

Delta Turbidity ANN Model (DASM-T) Development Using DSM2: Phase 3 Results



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TABLE OF CONTENTS

1	Introduction	1-1
2	Approach	2-1
2.1	Overall Approach.....	2-1
2.2	DSM2 Model.....	2-1
2.2.1	DSM2 Turbidity Model.....	2-1
2.2.2	Formulation of Boundary Condition Scenarios	2-2
2.3	Artificial Neural Network Model.....	2-2
2.3.1	Model Inputs	2-2
2.3.2	ANN Output Locations	2-7
2.3.3	ANN Model Structure	2-8
2.3.4	Training Dataset Division	2-10
3	Results	3-1
3.1	DSM2 Simulated Turbidity at Target Locations.....	3-1
3.2	Ann Training Results	3-1
3.3	Nonlinear Autoregressive Network (NARX)	3-4
3.4	Residuals Analysis	3-4
3.5	Sensitivity Analysis	3-6
3.6	Validation of ANN Networks with DSM2 Simulation	3-12
3.7	ANN Forecast For Wet Season of 2012/2013.....	3-15
3.8	Use of OMR Flow Modification to Control Turbidity.....	3-28
3.8.1	Multi-year Analysis (1975-2011).....	3-29
3.8.2	Analysis for the 2012-2013 Wet Season	3-31
3.8.3	Summary of Turbidity Control using OMR Flows.....	3-31
4	Summary and Discussion.....	4-1
5	References.....	5-1

ACRONYMS

ANN	Artificial Neural Network
CCF	Clifton Court Forebay
CCWD	Contra Costa Water District
CVP	Central Valley Project
DICU	Delta Island Consumptive Use
DSM2	Delta Simulation Model II
DWR	Department of Water Resources
FFW	Feedforward Network
FWS	Fish and Wildlife Service
IEP	Interagency Ecological Program
MWD	Municipal Water District
MLP	Multi-layer Perceptron
NARX	Nonlinear Autoregressive Network with Exogenous Inputs
NTU	Nephelometric Turbidity Units
OMR	Old and Middle River
RMA	Resources Management Associates

SE Standard Error

SWP State Water Project

WARMF Watershed Analysis and Risk Management Framework

EXECUTIVE SUMMARY

A 2008 Biological Opinion by the U.S. Fish and Wildlife Service (FWS) has recommended changes in the manner in which flows and freshwater exports through the Delta are managed to address the decline in population of the Delta smelt (*Hypomesus transpacificus*). Delta smelt abundance is related to various water quality parameters, including temperature, conductivity, and turbidity, possibly due to linkages between Delta smelt migration and turbidity levels. California Department of Water Resources (DWR) scientists have observed that there is an increase in Delta smelt salvage at the water export facilities when the turbidity exceeds a level of approximately 12 Nephelometric Turbidity Units (NTU). To support implementation of the 2008 Biological Opinion, there is a need to understand and predict fate and movement of turbidity in the Delta. The analysis presented here builds on existing modeling studies by developing an artificial neural network (ANN) model for turbidity in the Delta, with the goal of providing rapid estimates of turbidity for near-term forecasting and long-term planning studies.

Turbidity estimates across the Delta were generated using the Delta Simulation Model (DSM2) for a 35-year hydrology (1975-2011) and using 12 scenarios that took into account different levels of turbidity inputs at boundaries, as well as the presence and absence of exports. The boundary inputs of flow and turbidity, as well as the turbidity at sixteen designated locations were used as the training data set for the ANN. The training was performed using these synthetic data, rather than observed data, because the available observed data represent a relatively small period (2009-2013) and may not capture the full range of variability in the Delta.

The synthetic turbidity data were used to train two types of networks: feedforward networks that use only the boundary flow and turbidity values; and the autoregressive NARX network (for Nonlinear Autoregressive Network with Exogenous Inputs) structures, which used boundary values as well as antecedent in-Delta turbidity values. The training process included a partitioning of the data such that a subset of the data was always used for validation and testing of the trained ANNs (both feedforward and NARX). The trained networks, when compared to DSM2 results, showed good emulation

and were tested through correlations and evaluation of residuals against ANN inputs. The residuals analysis generally showed no correlation with flow or turbidity inputs, with higher residuals under lower flow. Evaluation was also performed for both the NARX and feedforward models using observed data for the 2012-13 wet season. The observed data were more challenging to fit using the ANNs although key features of the data, such as the peak turbidities were well represented. The NARX networks matched the magnitudes and durations of the observed turbidity peaks for this event reasonably well based on a visual comparison. The feedforward network fits, although not as good as the NARX fits, generally matched the same observed data. For predictive applications where only boundary conditions might be available, and the NARX model cannot be applied, the use of the feedforward network appears reasonable.

A sensitivity analysis of turbidities at various locations to OMR flow was conducted. The model showed different patterns of sensitivity to turbidity in different regions of the Delta. The West Delta stations showed no response or slight decrease in turbidity due to the increase of OMR flow. The Central Delta stations showed decreases in turbidity due to increases in OMR flow, while the South Delta showed mixed results of increasing turbidity to OMR flow under high turbidity input from the San Joaquin River and the opposite trend under low turbidity input from the San Joaquin River. The sensitivity analysis provides insight on the ability of the water project operations (through management of OMR flows) to affect turbidity at specific locations.

Use of the trained ANN networks to forecast turbidity during the wet season of 2012-13 demonstrated that the ANN networks closely followed DSM2 results, and the ANN behavior was similar to that obtained from DSM2 for the same stations. However, this behavior may not be matched by field observations, and may be related to the formulation of the mechanistic turbidity model in DSM2. Continued improvement of the underlying modeling and a larger database of observed turbidity may provide a basis for improvements to the ANNs in future years.

The feedforward ANN model was also used to explore conditions under which turbidity at selected compliance stations could be controlled by modifying the OMR flow. Using historical boundary flows and turbidities over 1975-2011 as inputs, the ANN model was first used to identify the potential turbidity exceedance events (three-station minimum turbidity exceeding 12 NTU for three continuous days), and in each case, the OMR flow was changed until the turbidity was decreased to below the threshold of 12 NTU. It was found that OMR flow could only control a subset of the events (9 out of 37, over a 35-year period). Separately, the 2012-13 wet season turbidity was analyzed using the same approach. This differs from the other periods because of the availability of observed data and the occurrence of high turbidities, conditions which came very close to it being considered a turbidity exceedance event using the definition of a three-station minimum turbidity exceeding 12 NTU for three days. Because two of the three stations had high turbidities for several days, the three-station minimum was in fact exceeded only for one

day, and, despite the visual impression, this does not fit the narrow definition of an exceedance event. This was true whether we looked at the observed data or the ANN-simulated data. The potential for turbidity control was explored because this event is recent and because of the high turbidities that resulted in two of the compliance stations (Prisoner's Point and Holland Cut). The OMR flow control approach shows that turbidity at these two stations could be decreased by changing the OMR flow but not below 12 NTU for the entire wet season. Although the turbidities are sensitive to OMR flow, in general, two factors preclude all events from being controlled: first, the range of available OMR flow for control is limited by the exports, and second, the relationship between OMR flow and turbidity is not monotonic, and in some cases reducing OMR flow may lead to higher turbidities at the compliance stations. These findings are of considerable importance for Delta operations, and next steps may include more mechanistic examination of the conditions where turbidity can and cannot be controlled.

1 INTRODUCTION

The Delta smelt (*Hypomesus transpacificus*) is an endangered species endemic to the Sacramento-San Joaquin estuary of California, with low recorded abundance in the last decade by the Interagency Ecological Program (IEP). A 2008 Biological Opinion by the U.S. Fish and Wildlife Service (FWS) recommended changes in the manner in which flows and freshwater exports through the Delta are managed to address the decline in population of this species (<http://www.fws.gov/sfbaydelta/ocap/>). Delta smelt abundance is related to various water quality parameters, including temperature, conductivity, and turbidity, possibly due to linkages between Delta smelt migration and turbidity levels (Armor and Sommer, 2006). California Department of Water Resources (DWR) scientists have observed that there is an increase in Delta smelt salvage at the water export facilities when the turbidity exceeds a level of approximately 12 Nephelometric Turbidity Units (NTU).

To support implementation of the 2008 Biological Opinion, there is a need to understand and predict fate and movement of turbidity in the Delta. Besides greater collection of turbidity data that has been initiated since 2009, turbidity modeling is also needed. Two such approaches include mechanistic modeling using the Delta Simulation Model (DSM2) (Liu and Sandhu, 2011) and using the Resource Management Associates RMA-2 model (RMA, 2008). These models compute turbidity within the Delta channels given inputs of flow and turbidity at all relevant boundaries. However, both modeling approaches require considerable user expertise and computational time to run, hence limiting their accessibility. There is an additional need for a tool that can be used to provide rapid predictions of turbidity in two situations: for near-term operations planning, where there is a need to estimate turbidity expected over subsequent days under a variety of operating scenarios, and, for long-term water supply planning, where there is a need to estimate turbidity-related export constraints in water operations models (e.g., CALSIM) run over multi-year periods. Under these conditions, running a fully mechanistic model of the system is generally not computationally feasible.

To fit this need for generating rapid predictions, Artificial Neural Networks (ANNs) were proposed as an alternative mathematical approach to conventional statistical methods and mechanistic models. ANNs use simple elements (neurons) and connections between elements using a range of functional forms to represent complex real-world data. The ANN methodology was inspired by biological nervous systems (Demuth and Beale, 2002) and has found broad application in the prediction and control of complex systems. An ANN can be trained, in a manner similar to calibrating a model, to perform a particular function through adjusting values that form the connections between elements (weights).

The ANN approach has been used broadly in the Sacramento–San Joaquin Delta in predicting salinity at various interior locations by the California Department of Water Resources (Finch and Sandhu, 1995; Sandhu et al., 1999) and for predicting salinity and impacts of sea level rise (Seneviratne et al., 2008). The salinity ANN developed by DWR was trained on DSM2 results that may represent historical or future conditions, through taking into account individual flow components and operational parameters as model inputs.

This work, i.e., the application of ANNs for turbidity modeling, was accomplished in two phases. Phase 1 of the Delta turbidity ANN model study explored the potential of developing an ANN turbidity model at a few locations within Delta, and to determine whether the methodology was suitable for broader-scale application. The study used model-calculated turbidity values from DSM2 for the period of 1990-2010 for training the ANN. Results from the Phase 1 work provided an important proof-of-concept of the use of ANNs for modeling turbidity in the Delta, and provided support for the use of the approach for planning and operational purposes (Chen and Roy, 2012). The ANN model was termed DASM-T, for Delta ANN Simulation Model-Turbidity.

Phase 3 of the work, presented in this report, extends previous phases of the work to use updated DSM2 calibration based on turbidity data of 2010-2013. Similar to the Phase 1 and 2 studies, the DSM2 model was used to create datasets for the ANN training, based on combinations of different turbidity levels at boundary locations. The Phase I study used a DSM2 model calibrated using turbidity data for the wet season of 2010 at various locations within the Delta (Liu and Sandhu, 2011). Phase 2 of the work extends Phase 1 analysis to include additional stations for a total of 16 stations within the Delta. An updated version of the DSM2 model, calibrated using extended record periods of flow and turbidity (2010-2013) by Resource Management Associates (RMA) was used in this phase of the study (RMA 2013). The RMA-calibrated version of the DSM2 model used extended periods of flow records and combinations of turbidity values from USGS (Freeport and Vernalis) and watershed model simulations at boundary locations (Calaveras, Mokelumne, Cosmunes and Yolo) to simulate turbidity for the 1975-2011 period. Watershed model simulations that are embedded in the boundary turbidity values were developed using the Watershed Analysis and Risk Management Framework

(WARMF) model. A total of 12 scenarios with different combinations of turbidity levels at boundary locations were used to generate datasets for training, following the approach used in the Phase 1 and Phase 2 work.

2 APPROACH

2.1 OVERALL APPROACH

The overall approach of the Phase 3 study, similar to Phase 1 and 2, was to train the ANN model based on a set of boundary scenarios formulated to represent historical or potential future conditions in the Delta, generated by the DSM2 model. The DSM2 model was selected to simulate turbidity within the Delta, rather than using the observed data directly. This is because the model is able to mechanistically simulate the response in turbidity at different Delta locations, due to changes in individual flow components and operating conditions that could potentially occur in the future. This range of responses may not be captured by using observed turbidity data available at these locations, which span a relatively short time frame (from 2009 to the present). The DSM2 model outputs are considered the next best option for developing a long-term data set that is able to account for future changes in Delta flow and operation under a reasonably wide range of hydrologic conditions. It is important to understand the initial goal of the present work is the emulation of DSM2 performance, with the testing and evaluation and performed against model-generated turbidity. More broadly, however, the ultimate goal is to represent the natural system, and the performance of the ANN can also be evaluated against new turbidity data, that are independent of DSM2 and of the dataset used for calibrating DSM2.

2.2 DSM2 MODEL

2.2.1 DSM2 TURBIDITY MODEL

An updated version of the DSM2 turbidity model developed by RMA was used to simulate turbidity within the Delta (RMA, 2013). The model was calibrated for the wet season of 2010, 2011 and 2012, using turbidity data available at 15-minute intervals, and using variable first-order decay rates through the Delta (varying in space, but constant in time). The model used a combination of suspended sediment data from USGS at Freeport and Vernalis and WARMF model output at other boundary locations (Yolo Bypass, the Calaveras, Cosumnes, and Mokelumne Rivers). Model simulated turbidity at 15-minute

intervals and daily average values were comparable to values observed at a number of locations including the Sacramento River at Rio Vista, Decker Island, Prisoner's Point, Holland Cut, San Joaquin River at Jersey Point, Garwood, Mossdale, Brandt Bridge, and Old River at Bacon Island, and Victoria Canal.

2.2.2 FORMULATION OF BOUNDARY CONDITION SCENARIOS

The updated DSM2 turbidity model was used for simulating flow and turbidity relationships within the Delta under a set of formulated boundary scenarios. The DSM2 model was run for a period of 36 years assuming observed hydrology and water project operations from 1975–2011. The formulated boundary scenarios take into account combinations of different turbidity levels (low, middle, and high levels) from three sources: North Delta (Sacramento River + Yolo), San Joaquin River, and east side tributaries (Mokelumne, Cosumnes, and Calaveras Rivers). Turbidity from Delta Islands and Martinez locations were set as constants. The boundary scenarios also considered the effect of removing water project diversions. A total of 12 scenarios were formulated (Table 2-1). Historical water project operations were modified assuming that: 1) the Delta Cross Channel (DCC) gate is closed all months; and 2) south Delta temporary barriers are not installed. The assumptions are reasonable given that the ANN model will be used for the period of December through February. Detailed flow-turbidity relationships used to determine boundary turbidity inputs under low, middle or high turbidity conditions at different boundary locations are listed in Appendix A. The derived boundary conditions for the low, middle and high turbidity levels are shown graphically in Figure 2-1.

2.3 ARTIFICIAL NEURAL NETWORK MODEL

2.3.1 MODEL INPUTS

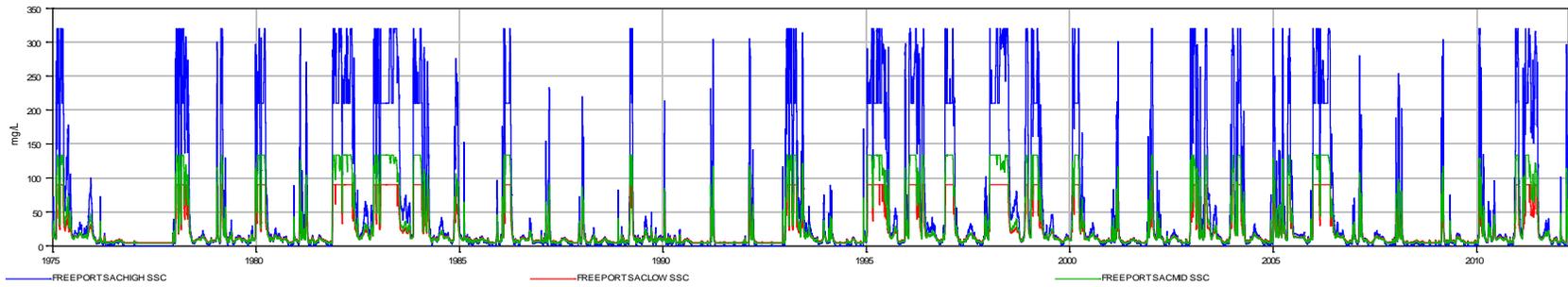
For the ANN model training, a set of six input variables were used. These input variables are considered to be the main boundary conditions that influence turbidity dynamics within Delta. These inputs include:

- North delta inflow
- East side stream inflow
- Calculated Old and Middle River (OMR) flow
- North delta turbidity
- East side stream turbidity
- San Joaquin River (Vernalis) turbidity

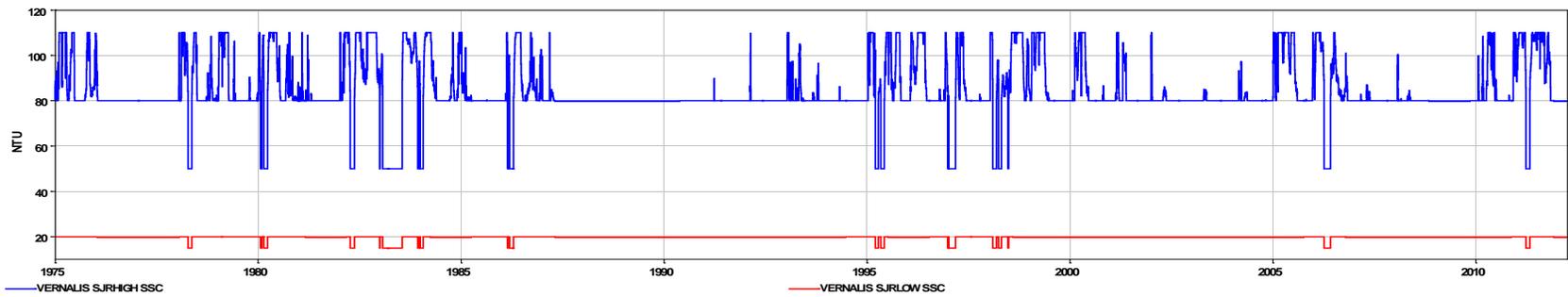
Table 2-1
DSM2 Simulations and Associated Turbidity
Boundary Conditions Used for Generating ANN Training Data

Run	Hydrology	Sacramento	SJR	Yolo	Cosumnes	Mokelumne	Calaveras	Islands	Martinez
1	Historical	Low	Low	Low	Low	Low	Low	10 ntu	26.6 ntu
2	Historical	Mid	Low	Mid	Mid	Mid	Mid	10 ntu	26.6 ntu
3	Historical	High	Low	High	High	High	High	10 ntu	26.6 ntu
4	Historical	Low	High	Low	Low	Low	Low	10 ntu	26.6 ntu
5	Historical	Mid	High	Mid	Mid	Mid	Mid	10 ntu	26.6 ntu
6	Historical	High	High	High	High	High	High	10 ntu	26.6 ntu
7	Historical w/o Exports	Low	Low	Low	Low	Low	Low	10 ntu	26.6 ntu
8	Historical w/o Exports	Mid	Low	Mid	Mid	Mid	Mid	10 ntu	26.6 ntu
9	Historical w/o Exports	High	Low	High	High	High	High	10 ntu	26.6 ntu
10	Historical w/o Exports	Low	High	Low	Low	Low	Low	10 ntu	26.6 ntu
11	Historical w/o Exports	Mid	High	Mid	Mid	Mid	Mid	10 ntu	26.6 ntu
12	Historical w/o Exports	High	High	High	High	High	High	10 ntu	26.6 ntu

a. Sacramento River



b. San Joaquin River



c. Yolo Bypass

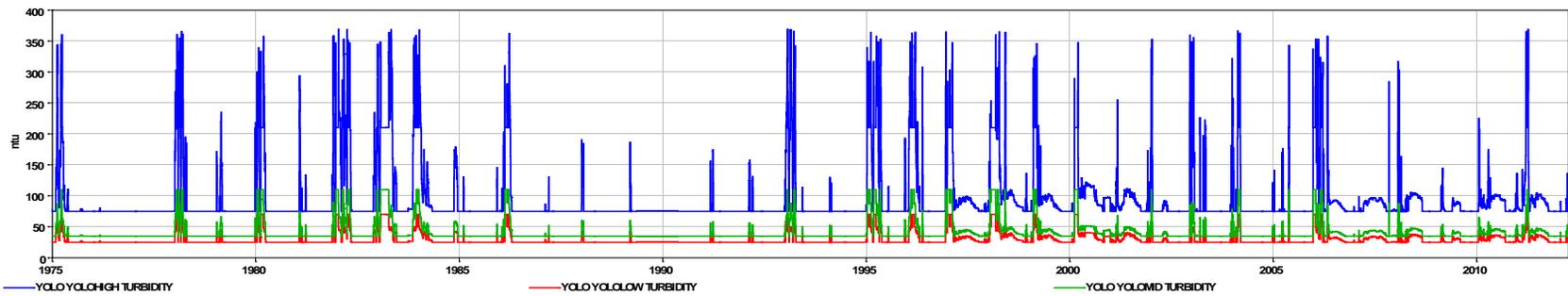
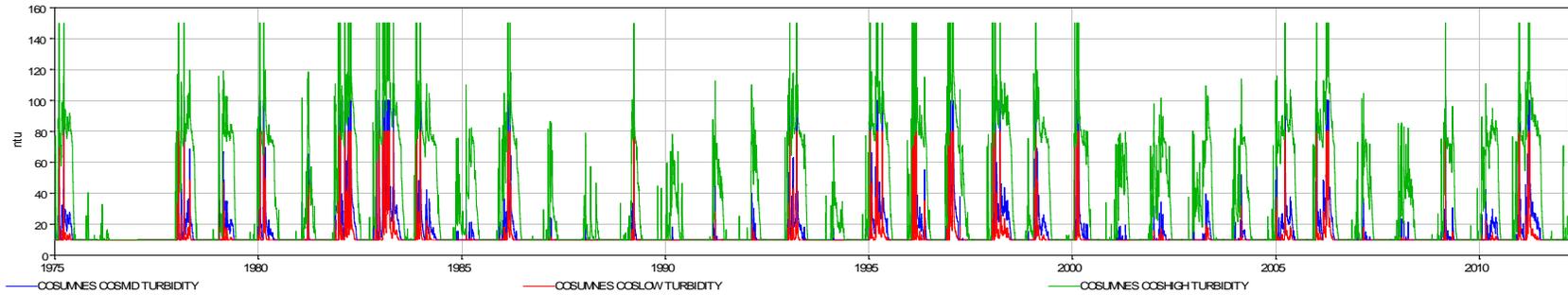
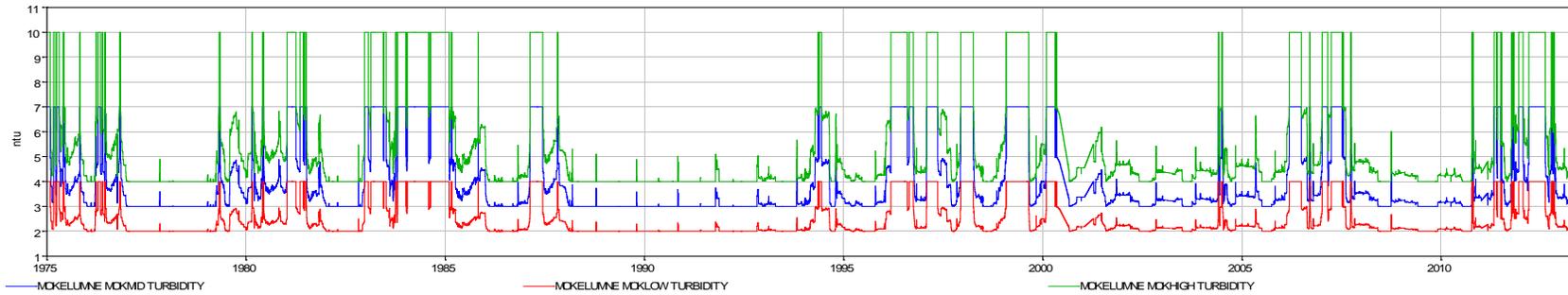


Figure 2-1 Boundary conditions of low, middle, and high turbidity levels at: a) Sacramento River; b) San Joaquin River; c) Yolo Bypass; d) Cosumnes; e) Mokelumne, and f) Calaveras Rivers.

d. Cosumnes River



e. Mokelumne River



f. Calaveras River

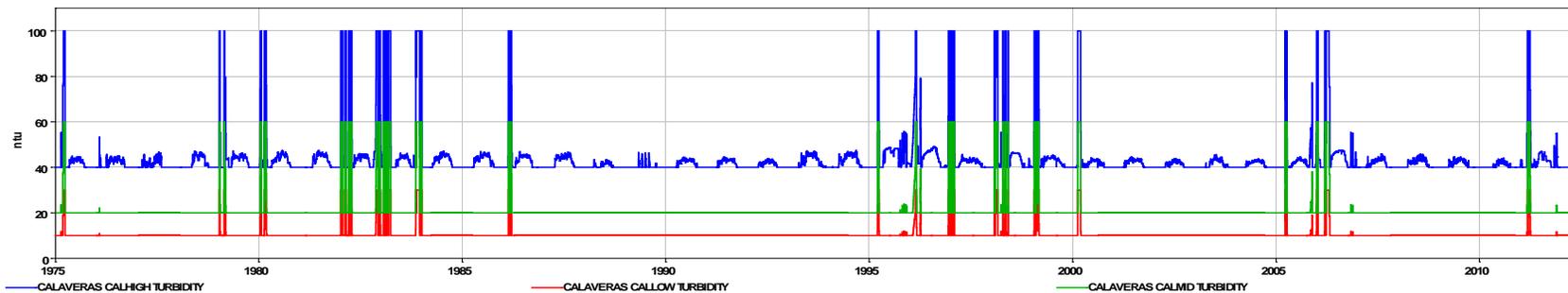


Figure 2-1 (continued) Boundary conditions of low, middle, and high turbidity levels at: a) Sacramento River; b) San Joaquin River; c) Yolo Bypass; d) Cosumnes; e) Mokelumne, and f) Calaveras Rivers.

The north delta inflow was calculated as the total of the Sacramento River and Yolo Bypass inflow. The east side stream flow was calculated as total of inflow from the Mokelumne River, the Cosumnes River and the Calaveras River. The current configuration of the Delta relies on the Old and Middle Rivers to convey water to the CVP-SWP export pumps. This pathway can result in reverse flows and have significant impacts on water project operations (Hutton, 2008). A south Delta water balance was used in determining OMR flows:

OMR flow = San Joaquin River flow at Vernalis

+ Indian Slough flow at Old River

– San Joaquin River flow downstream of HOR

– Clifton Court Forebay diversions

– Jones pumping plant diversions

– CCWD Old River intake diversions

– South Delta net channel depletion

When calculating the OMR flow, DSM2 boundary conditions were used for San Joaquin River flows at Vernalis, diversions at Jones Pumping Plant and CCWD Old River intake (Hutton, 2008). Computed data from DWR's Delta Island Consumptive Use (DICU) model were used in the water balance for south Delta net channel depletions. DSM2 simulated data were used in water balance calculation for flows at Indian Slough at Old River, San Joaquin River downstream of HOR (Head of Old River) and diversions at Clifton Court Forebay (CCF). A detailed approach for calculating the OMR flow was outlined by Hutton (2008) and described in the Phase 1 report (Chen and Roy, 2012).

A calculated OMR flow is used as it will allow for a more explicit relationship between exports and hydrodynamic conditions. This relationship is needed as forecast scenarios will be based on different operation scenarios. Phase I work of this study showed that DSM2 generated OMR values did not provide improvements over calculated OMR values.

The north Delta turbidity was calculated as flow-weighted averages of turbidities at the Sacramento River at Freeport and Yolo Bypass. The east side stream turbidity was calculated as flow weighted averages of turbidities at the Mokelumne, Cosumnes, and Calaveras Rivers. Turbidity from these tributaries and San Joaquin River at Vernalis was computed based on flow - turbidity relationship derived from an analysis (outlined in Appendix A) for low, middle and high turbidity input levels (RMA, 2013).

2.3.2 ANN OUTPUT LOCATIONS

Phase 2 of the work expanded the turbidity ANN locations in the Delta to a total of 16 stations (Figure 2-2). These stations include:

- West Delta
 - Sacramento River @ Rio Vista
 - Sacramento River @ Decker Island
 - SJR @ Jersey Point
- Central Delta
 - SJR @ Prisoner's Point
 - Old River @ Holland
 - Old River @ Quimby
 - Old River @ Bacon
 - Middle River @ Holt
 - Middle River @ Bacon Island
 - Turner Cut @ Holt
- South-Southeast Delta
 - Old River @ Hwy 4
 - Old River @ Clifton Court Intake
 - Victoria Canal
 - Middle River @ Union Point
 - Grant Line Canal @ Tracy
 - San Joaquin River @ Garwood

The DSM2 model simulates turbidity at locations throughout the Delta, a subset of which were used for this work. DSM2 output at 15-minute intervals was used to compute daily averages for the ANN training. DSM2 simulations of turbidity at the selected locations were used in training and for developing the Delta turbidity ANN model.

The training data set consisted of values over a 36-year hydrologic period for 12 boundary conditions, representing $\sim 365 \times 36 \times 12$ (=157,764) data points for each output location.

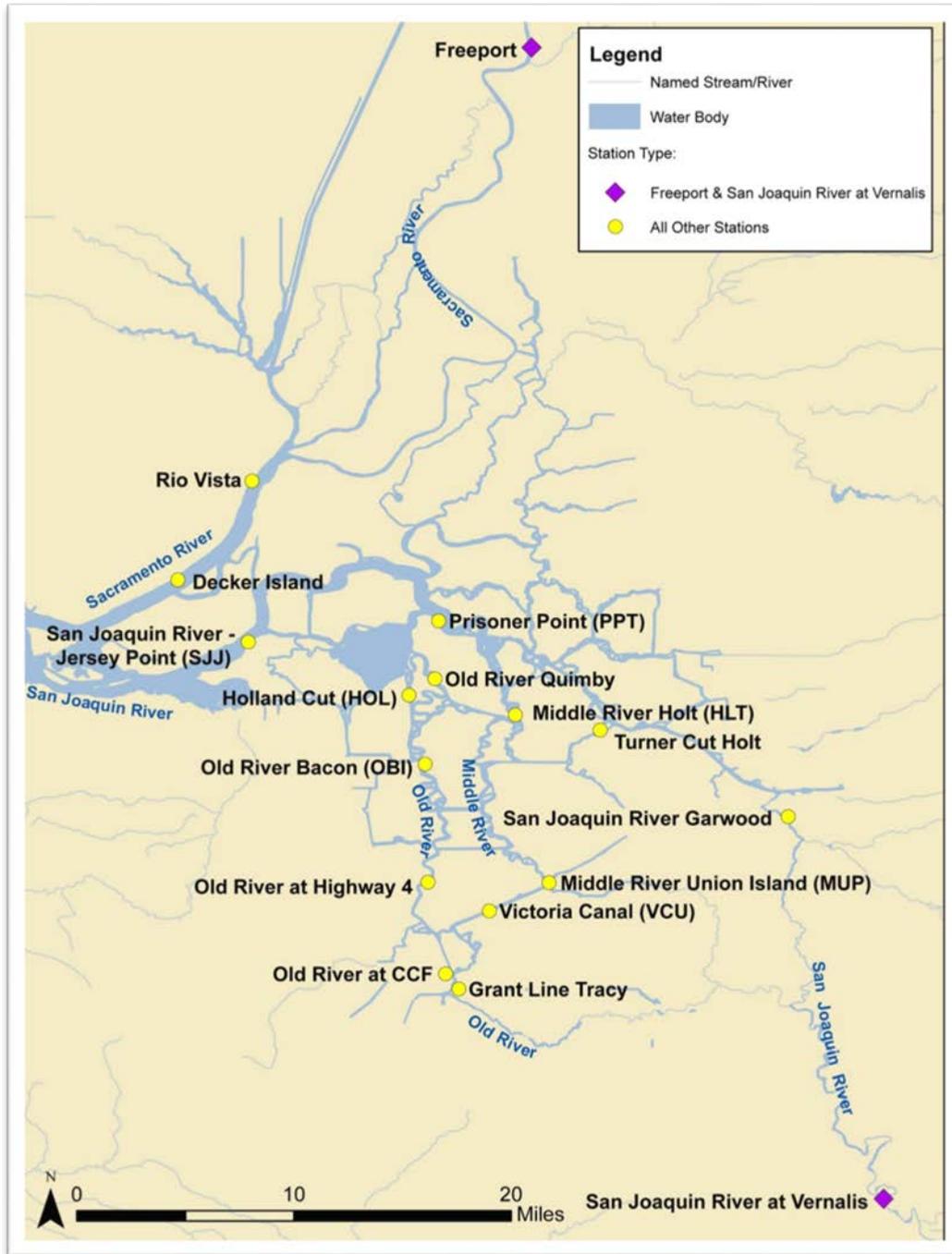


Figure 2-2 Locations of output stations for ANN training. Three letter codes, where shown, refer to CDEC station codes.

2.3.3 ANN MODEL STRUCTURE

The dynamic nature of flow and turbidity in the Delta requires a network structure that takes into account the time-series effect. Although other network structures have received attention in the recent literature, the multi-layer perceptrons (MLPs) are by far the most popular network structure used in water resources applications to date, representing more

than 90% of peer-reviewed applications in the water resources field (Maier et al. 2010). For this reason, the feedforward MLP network was selected in this study, and is shown schematically in Figure 2-3.

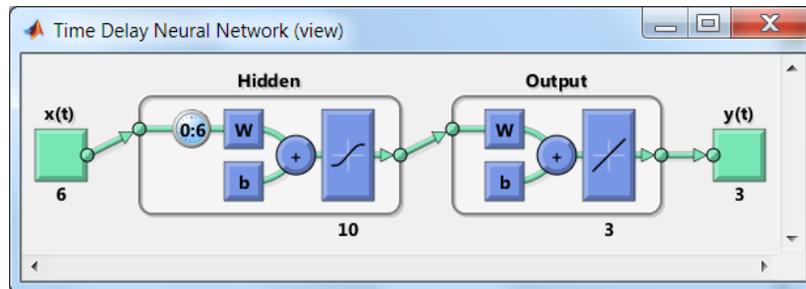


Figure 2-3 Feedforward ANN model structure (inputs = 6 boundaries (3 flow + 3 turbidity), hidden neurons = 10; time delay = 7 days; outputs: turbidity at 3 locations). $x(t)$ represents the input, $y(t)$ the output, and W and b represents the weights and biases.

In this network, the input layer, termed $x(t)$ contains time series of six input variables (3 flow inputs, and 3 turbidity inputs as described earlier). The hidden layer uses 10 neurons, which is formulated based on input variables using a set of weights (W) and biases (b). For 10 neurons and 6 input variables, this will yield a total of 60 weights and 60 bias parameters that need to be adjusted during training. An input time delay of 1–4 days can be used, each with its own set of weights and bias parameters. For a time delay of 4 days, the network will yield 240 weights and 240 bias parameters. The output layer, $y(t)$, contains the number of output variables defined for each ANN. The hidden layer is converted to the output layer through another set of weights and biases.

In addition to the feedforward network, the turbidity data were also fitted to a nonlinear autoregressive network with exogenous inputs (NARX) network, where the output of the model at the previous time steps is also used as an input as shown on the left side of Figure 2-4. The NARX network training can be implemented in what is termed the “open loop” mode, where the output data are used for training. Once the model is trained, it can be converted to a “closed loop,” where the values of $y(t)$ on the left side are obtained from ANN for the previous time step.

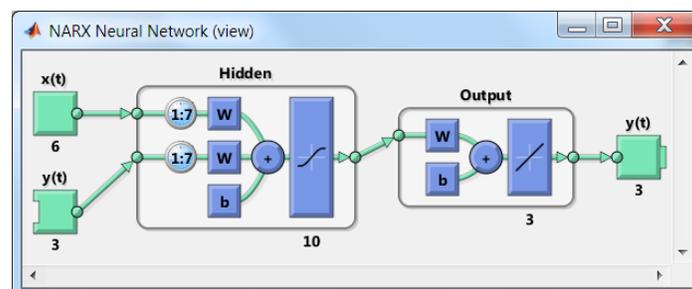


Figure 2-4 Matlab NARX ANN model structure ($y(t) = f(x(t-1), \dots, x(t-d))$); inputs = 6 boundaries (3 flow + 3 turbidity), hidden neurons = 10; time delay = 1-7 days; outputs: turbidity at 3 locations). During training, $y(t)$ on the left side can be approximated by the training data (termed “open loop”), and during testing, $y(t)$ can be replaced by the ANN predicted value (termed “closed loop”).

2.3.4 TRAINING DATASET DIVISION

DSM2-simulated turbidity at sixteen locations of interest in the Delta from the twelve scenarios was used as training targets. During the training process, the model development dataset is usually divided into training, validation and testing purposes. The training dataset is used to compute the gradient and determine the model parameters (weights and bias). The validation dataset is used during training to find the minimum error point and prevent over-training. An error is monitored on the validation dataset during training. The validation error normally decreases during the initial phase of training, as does the training set error. However, when the network begins to over-fit the data, the error on the validation set typically begins to rise. When the validation error increases for a number of iterations, the training is stopped, and the parameters at the minimum validation error are returned. The test dataset is not used in the training or validation (e.g., for stopping the network) and provides an independent evaluation on network performance.

In this work, the data were divided in the following manner: 60%, 20%, and 20% was used for training, validation and testing, respectively. The data points for training, validation and testing were randomly selected from the entire dataset for each training cycle.

3 RESULTS

3.1 DSM2 SIMULATED TURBIDITY AT TARGET LOCATIONS

The updated DSM2 model from RMA was run using the formulated 12 scenarios of boundaries described in Chapter 2, for a time period of 36 years from 1975-2011. The simulated turbidity time series at sixteen target locations for each of the twelve scenarios are presented in Appendix B. These simulated turbidity values were used as targets in the ANN training. The goal of the training is to minimize errors between the ANN simulated and target turbidity simulated by DSM2 at each location.

3.2 ANN TRAINING RESULTS

The ANN training was conducted using the feedforward time series network with time delay. Because it can take several days for particles to travel from one location to the other location within the Delta as shown in the monitoring data, a time lag of 5-10 days in the inputs of the ANN model is desired. Therefore, for all the subsequent training, a time delay of 5-10 days was used, depending on location. The number of neurons used was 10. The results for performance of all data, training, validation and test for one example training are shown in Figure 3-1.

Time-series comparison and daily/monthly scatter plots of ANN trained and DSM2 simulated turbidity are shown for each station in Appendix C. The model performance (measured in terms of R^2 and standard error, SE) of the feedforward network is shown in Table 3-1.

The model fit for the West Delta stations is generally good, with R^2 between 0.96-0.99 for daily time step. The fit for Central Delta is slightly lower, with R^2 ranging from 0.85 – 0.90 for the daily time step. The South Delta stations show relatively good fit with R^2 between 0.88-0.94 for the daily time step. The fit at Old River at Clifton Court Intake station is lower among the south Delta stations. This is likely due to flow management at this location that is more difficult to capture both by the DSM2 and ANN model.

The results suggested that an ANN model structure of feedforward network with 10 neurons and 5-10 days of delay resulted in relatively good model fit at various Delta locations. The fit for most of the stations are good ($R^2 > 0.90$), with some stations showing slightly poorer fits ($R^2 = 0.85-0.90$).

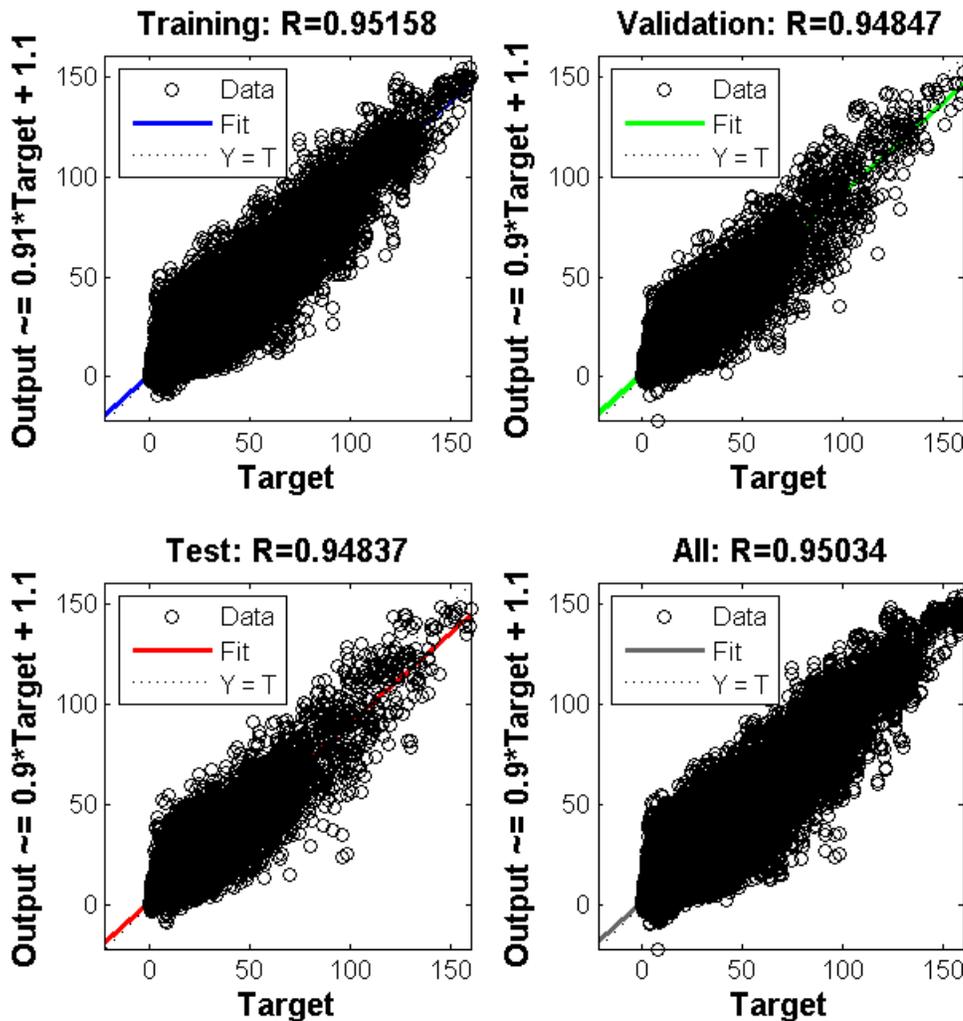


Figure 3-1 Correlation between trained and DSM2 simulated turbidity for the training, validation and test dataset for feedforward network training.

Table 3-1
Comparison of ANN and DSM2 Simulated Turbidity at Delta Locations (FFW)
ANN Turbidity (ntu) = $\Phi 1 + \Phi 2 * \text{DSM2 turbidity (ntu)}$

Location	Daily				Monthly			
	$\Phi 2$	$\Phi 1$	R ²	SE	$\Phi 2$	$\Phi 1$	R ²	SE
West Delta								
Sacramento River @ Rio Vista	0.9955	0.1923	0.9956	3.758	0.9945	0.2286	0.999	1.420
Sacramento River @ Decker Island	0.9949	0.2213	0.995	3.747	0.9919	0.3123	0.9986	1.550
SJR @ Jersey Point	0.9649	0.4918	0.965	4.314	0.9592	0.5749	0.9902	1.859
Central Delta								
SJR @ Prisoner's Point	0.9062	0.7651	0.9068	3.566	0.9187	0.6628	0.9676	1.618
Old River @ Holland	0.9542	0.5181	0.9544	3.226	0.9519	0.5418	0.9855	1.322
Old River @ Quimby	0.9281	0.7525	0.9296	4.058	0.9244	0.7913	0.9747	1.883
Old River @ Bacon	0.9954	0.5455	0.9555	3.387	0.9673	0.4019	0.9890	1.167
Middle River @ Holt	0.9005	0.8722	0.898	3.736	0.9269	0.6492	0.962	1.675
Middle River @ Bacon Island	0.9326	0.5737	0.9319	3.187	0.9406	0.5022	0.978	1.348
Turner Cut @ Holt	0.8798	1.2782	0.8801	4.805	0.9028	1.028	0.955	2.298
South-Southeast Delta								
Old River @ HWY4	0.9564	0.5928	0.9549	3.538	0.9663	0.459	0.987	1.258
Old River @ Clifton Court Intake	0.9164	1.3724	0.9156	5.375	0.9332	1.096	0.974	2.048
Victoria Canal	0.9539	0.4529	0.9534	3.027	0.9667	0.334	0.986	1.181
Middle River @ Union Point	0.9378	0.6036	0.9376	3.446	0.9374	0.6039	0.9782	1.529
Grant Line Canal @ Tracy	0.9567	1.3723	0.9559	5.247	0.8858	3.6064	0.9351	3.123
SJR @ Garwood	0.9542	0.8969	0.9537	4.860	0.9182	1.598	0.969	2.703

3.3 NONLINEAR AUTOREGRESSIVE NETWORK (NARX)

An alternative network structure, the autoregressive NARX network, was also used in the ANN training. The NARX network used output values the Delta stations from previous time steps as inputs to the model, and therefore generally has higher model performance.

The detailed comparison of trained ANN model results using the NARX network and the DSM2 model at each station is shown in Appendix D. The NARX model performance (in terms of R^2 and SE) is summarized in Table 3-2. The NARX model generally showed an R^2 of greater than 0.99 for most stations.

3.4 RESIDUALS ANALYSIS

Residuals are defined as the difference between the daily ANN and DSM2 simulated turbidity values at each station. The residuals at each station for the feedforward network and the NARX network were evaluated against the input variables for possible structure in the errors between ANN predicted and DSM2 simulated values. A spearman correlation was used to evaluate the correlation between residuals and the input variables. When no correlation and structure were found, the residuals were considered as random and no additional training was needed.

The residuals analysis was conducted by plotting residuals with respect to six inputs for the ANN model: three flow and three turbidity values. The results for the feedforward network and the NARX network are presented in Appendix E and F, respectively. For the feedforward network, residuals for the stations generally showed no correlation with turbidity inputs from the North Delta, east side streams and Vernalis (spearman correlation coefficient $|r| < 0.2$), and appear random. Patterns of relationships between residuals and turbidity inputs are generally similar among stations. The residuals appear slightly higher at low turbidities from the east side streams, suggesting the fit for the ANN model was better for higher turbidity inputs from the east side streams. Correlation between residuals and flow inputs at each station is also low, and appears random. The patterns of correlation between residuals and flow are similar among stations. There is a tendency of somewhat higher residuals at very low flow inputs. This suggests that for the months of interest for the turbidity model, which are the relatively high flow months of December through March, the ANN model emulation of DSM2 is better than the dry months of year.

Table 3-2
Comparison of ANN and DSM2 Simulated Turbidity at Delta Locations (NARX)
ANN Turbidity (ntu) = $\Phi 1 + \Phi 2 * \text{DSM2 turbidity (ntu)}$

Location	Daily				Monthly			
	$\Phi 2$	$\Phi 1$	R ²	SE	$\Phi 2$	$\Phi 1$	R ²	SE
West Delta								
Sacramento River @ Rio Vista	0.9992	0.0331	0.9991	1.670	0.9999	0.0117	0.9999	0.298
Sacramento River @ Decker Island	0.9995	0.0248	0.9991	1.612	0.9998	0.0129	0.9999	0.233
SJR @ Jersey Point	0.9957	0.0815	0.997	1.286	0.9981	0.045	0.9999	0.165
Central Delta								
SJR @ Prisoner's Point	0.9955	0.0442	0.9955	0.820	0.9993	0.0132	0.9999	0.099
Old River @ Holland	0.9984	0.0221	0.9985	0.604	0.9989	0.0166	0.9999	0.069
Old River @ Quimby	0.9961	0.0236	0.9966	0.922	0.9986	-0.0029	0.9999	0.118
Old River @ Bacon	0.9988	0.0221	0.9983	0.674	1.0000	0.0075	0.9999	0.065
Middle River @ Holt	0.9982	0.0239	0.998	0.552	1.0000	0.0084	0.9999	0.055
Middle River @ Bacon Island	0.9978	0.0241	0.9981	0.550	0.9993	0.0110	0.9999	0.071
Turner Cut @ Holt	0.9957	0.0549	0.9958	0.958	0.9990	0.0195	0.9999	0.103
South-Southeast Delta								
Old River @ HWY4	0.9972	0.0131	0.9963	1.032	1.000	-0.0255	0.9999	0.098
Old River @ Clifton Court Intake	0.9843	0.2451	0.9857	2.313	0.993	0.0997	0.9997	0.227
Victoria Canal	0.9961	0.0383	0.9962	0.884	0.998	0.0144	0.9999	0.096
Middle River @ Union Point	0.9973	0.0268	0.9972	0.751	0.9978	0.0223	0.9999	0.100
Grant Line Canal @ Tracy	0.9981	0.0701	0.9982	1.082	0.9961	0.1349	0.9999	0.135
SJR @ Garwood	0.9974	0.0625	0.9975	1.160	0.9969	0.0732	0.9999	0.174

The residuals for the NARX network were evaluated in the same manner. In absolute terms, residuals from the NARX network were generally lower than the feedforward network (Appendix F). Similar patterns of no correlation between residuals and inputs of turbidity were found for the NARX network. This suggests little structure in the residuals due to turbidity inputs. There is also a tendency of greater residuals under low flow inputs, similar to that noted for the feedforward networks. The results therefore suggest better emulation of the DSM2 model during high flow months of interest.

3.5 SENSITIVITY ANALYSIS

The trained ANN networks for feedforward network were tested for sensitivity with respect to OMR flows under different turbidity levels at the boundary locations, with other these inputs set at steady state levels. The sensitivity analyses were conducted for the following conditions:

- OMR flows of -8000 to 1,000 cfs, with 1,000 cfs increments
- North Delta turbidity at three levels of 50, 100 and 150 NTUs
- Vernalis turbidity of 30 and 100 NTUs
- North Delta inflow of 30,000 cfs
- East side stream inflow of 1,500 cfs
- East side turbidity of 30 NTUs

The sensitivity analysis results are shown for stations in the West Delta, Central Delta and South Delta (Figure 3-2 to Figure 3-4). The analysis showed a general pattern of increase in turbidities at stations with higher North Delta and San Joaquin turbidity inputs. The sensitivity of turbidity to OMR flow varies among stations.

The West Delta stations showed no sensitivity or decreases in turbidity with respect to increases in OMR flows (i.e. -8000 cfs to -1000 cfs; Figure 3-2). The Central Delta stations showed significant decreases in turbidity with increases in OMR flows (i.e. -8000 cfs to -1000 cfs) at several stations: Prisoner Point, Holland Cut, Old River at Quimby Island, Old River at Bacon Island, Middle River at Holt and Middle River at Bacon Island (Figure 3-3).

The South Delta stations and one station in the Central Delta (Turner Cut Holt) showed an increase in turbidity at stations with increases in OMR flow (i.e. -8000 cfs to -1000 cfs) and reverse trends under positive OMR flows under high turbidity input from the San Joaquin River (Figure 3-4). Under low turbidity input from San Joaquin, the South Delta stations showed opposite trend of decreasing turbidity with OMR (i.e. -8000 cfs to -1000 cfs) and reverse trends under positive OMR flow.

An identical steady state sensitivity analysis was conducted for the NARX closed network. The results are not identical to what was found with the feedforward network

although the broad patterns are similar (Figure 3-5 to Figure 3-7). Similar to the feedforward network, some stations in the Central and South Delta exhibited non-monotonic behavior (e.g., Turner Cut Holt, Victoria Canal, Middle River at Union Point).

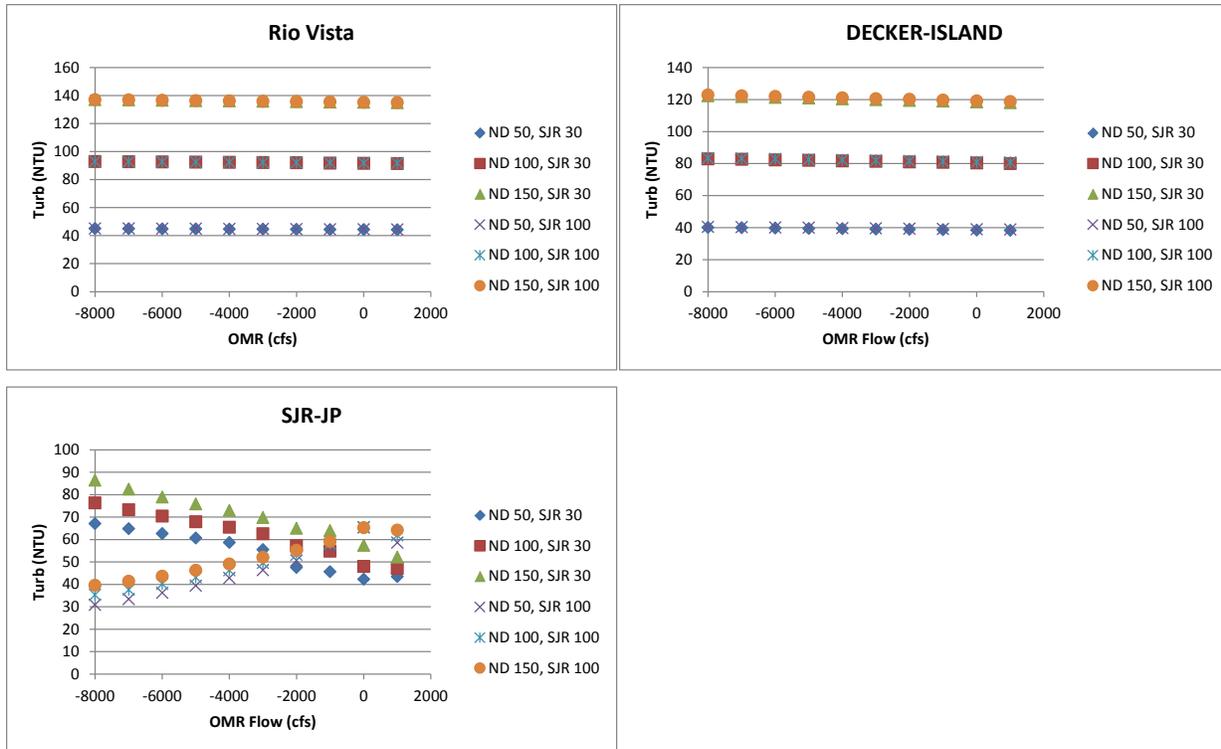


Figure 3-2 Sensitivity of FFW network turbidity at West Delta stations to OMR flow under different turbidity levels at North Delta and San Joaquin River at Vernalis

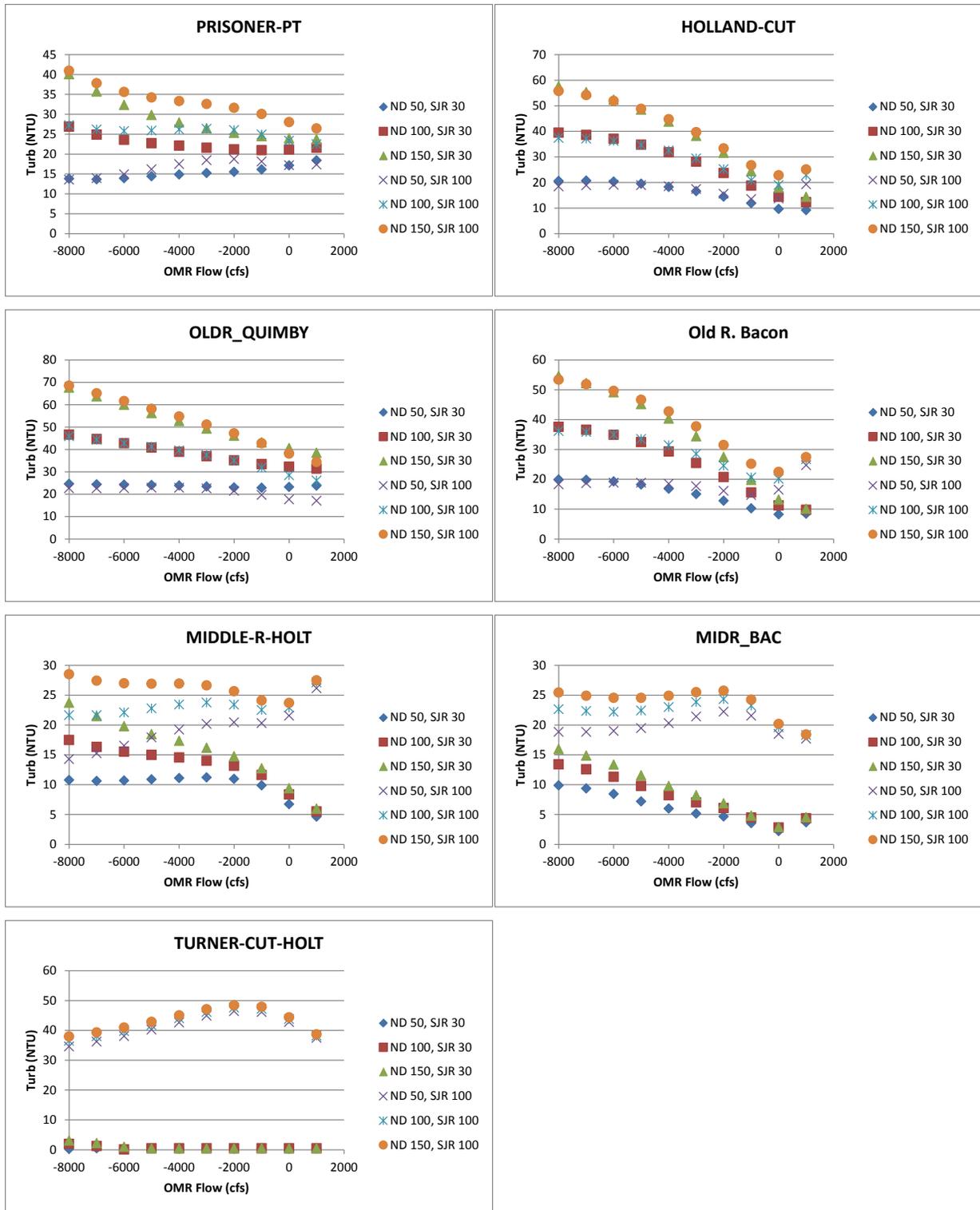


Figure 3-3 Sensitivity of FFW network turbidity at Central Delta stations to OMR flow under different turbidity levels at North Delta and San Joaquin River at Vernalis

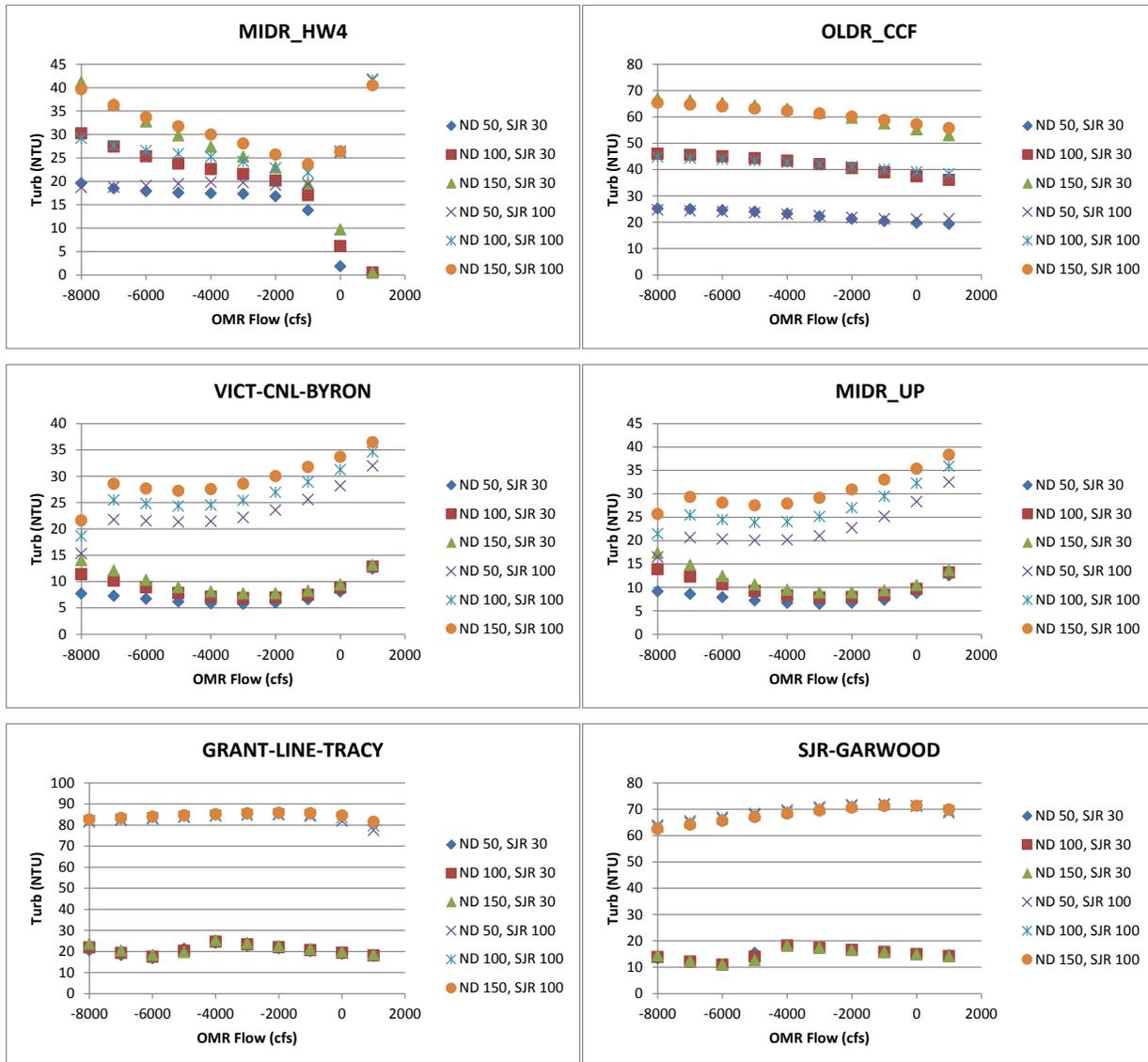


Figure 3-4 Sensitivity of FFW network turbidity at South Delta stations to OMR flow under different turbidity levels at North Delta and San Joaquin River at Vernalis

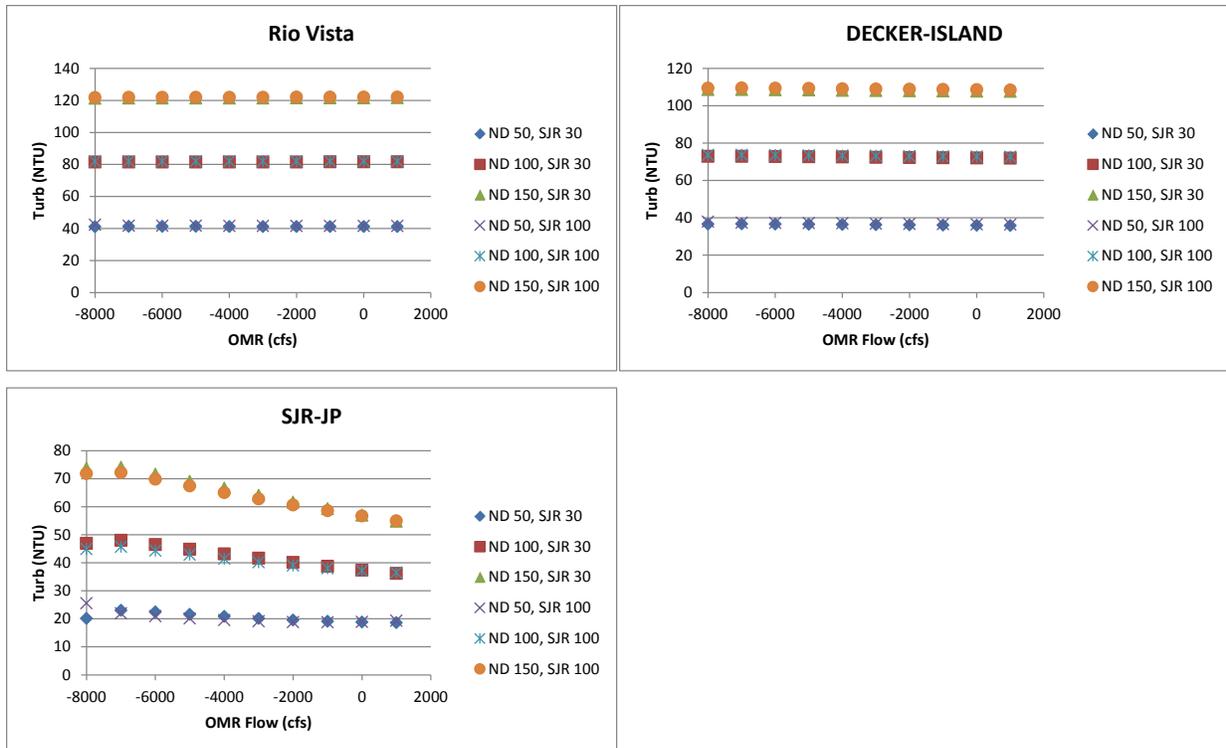


Figure 3-5 Sensitivity of NARX closed network turbidity at West Delta stations to OMR flow under different turbidity levels at North Delta and San Joaquin River at Vernalis

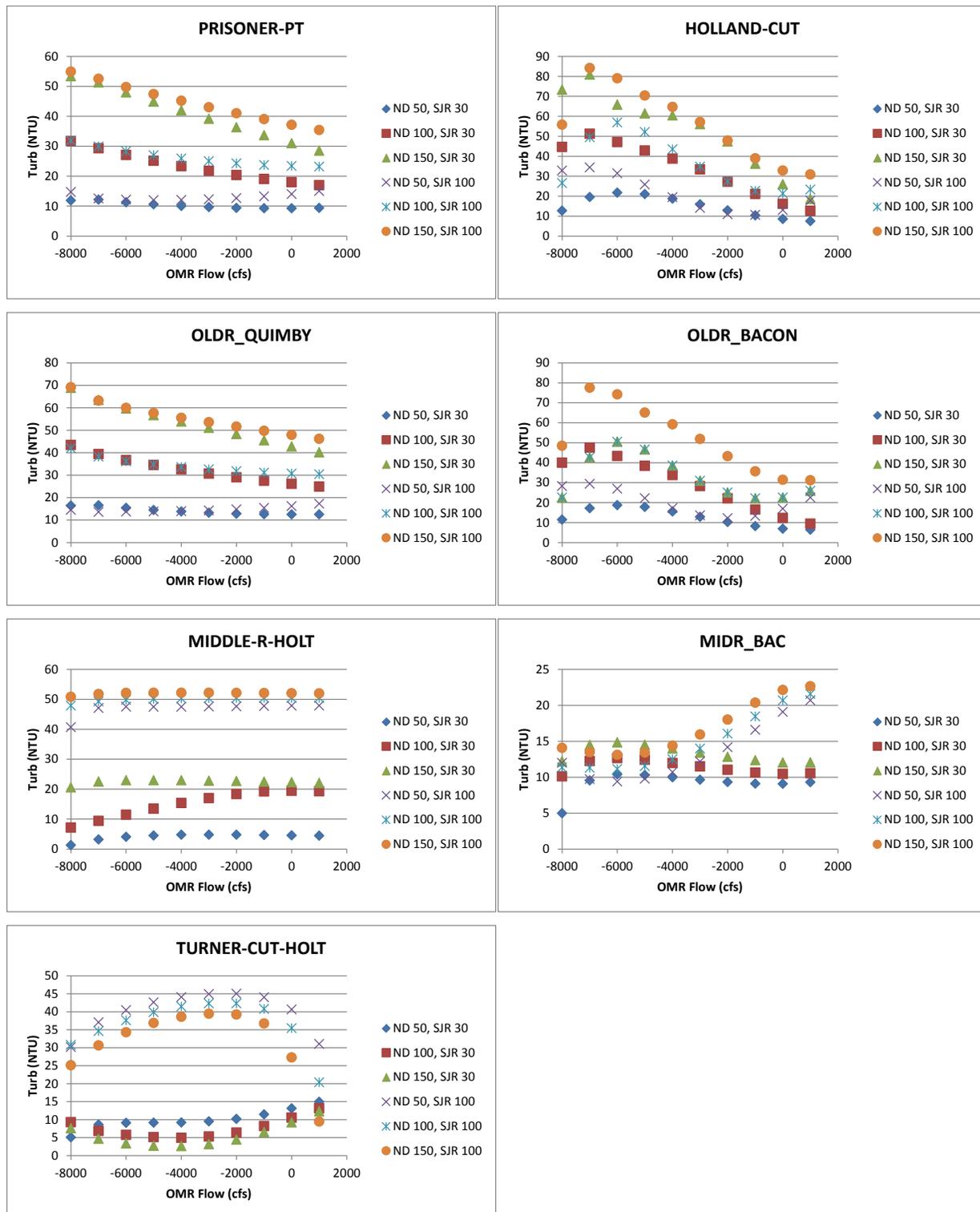


Figure 3-6 Sensitivity of NARX closed network turbidity at Central Delta stations to OMR flow under different turbidity levels at North Delta and San Joaquin River at Vernalis

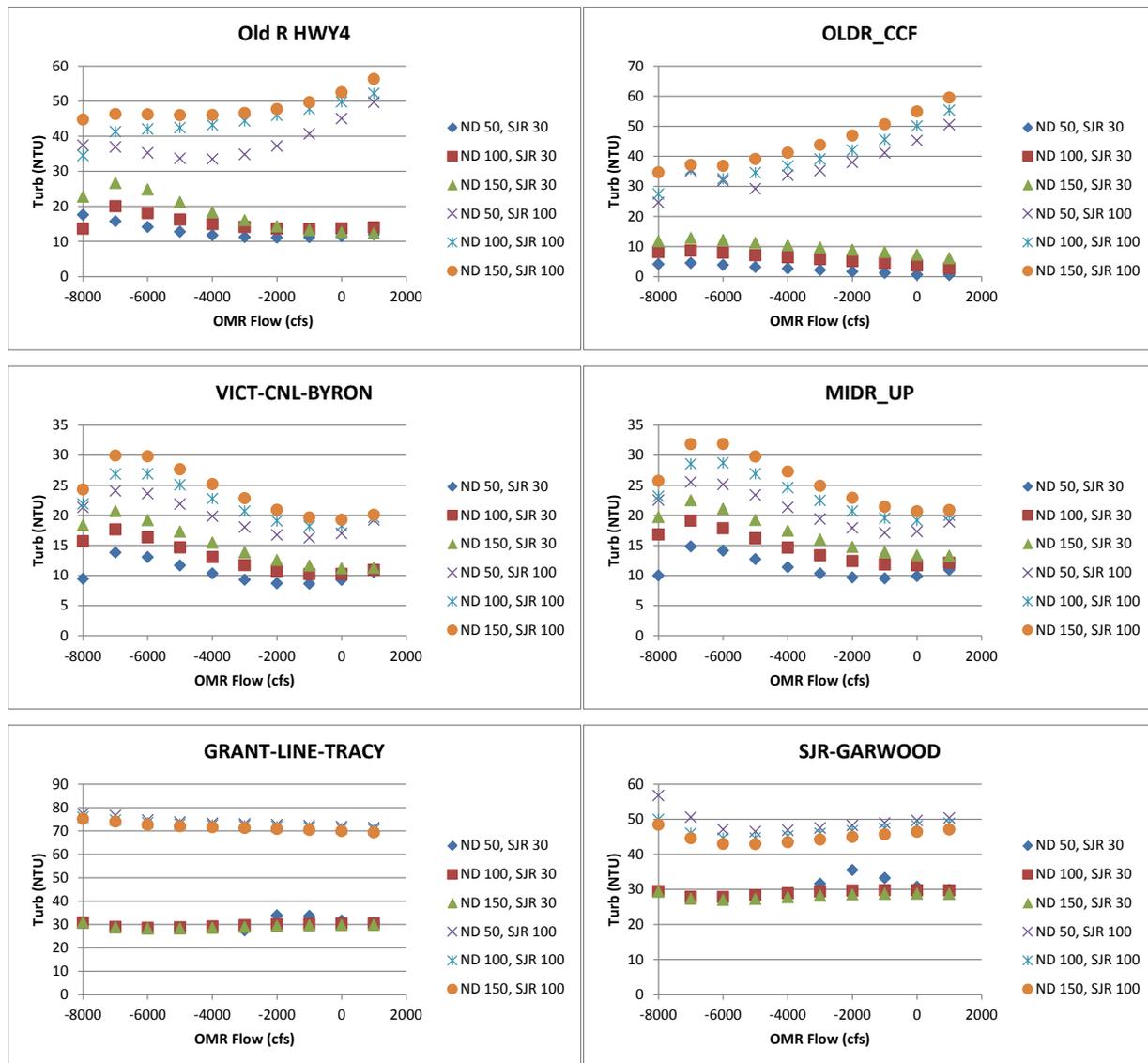


Figure 3-7 Sensitivity of NARX closed network turbidity at South Delta stations to OMR flow under different turbidity levels at North Delta and San Joaquin River at Vernalis

3.6 VALIDATION OF ANN NETWORKS WITH DSM2 SIMULATION

The trained NARX network was validated against the multi-year simulation from DSM2 during wet months for a long period of 1975-2011, based on estimated inputs of flow and turbidity (RMA 2013). These boundary conditions are different from those used in the training of the ANN and this test constitutes an independent validation of the trained ANN. The ANN results were compared to DSM2 simulated results on daily values and monthly averages for the months of December to February. The results for the NARX network (open) suggested good agreement between ANN and DSM2 results for monthly values ($R^2 > 0.95$; Table 3-3). Fits with daily values were generally poorer than with the monthly values. The comparison of time-series predictions of the ANN and DSM2 models for the wet seasons of 1975-2011 at representative locations is shown in Figure 3-8. The comparison suggests that the ANN model is able to closely emulate DSM2

results during critical months from December to February for a set of boundary turbidity inputs that are different what was used for training. Scatter plots corresponding to these time series comparisons are shown in Appendix G.

Table 3-3
Comparison of Daily and Monthly Averages of ANN and DSM2 Simulated Turbidity at Delta Locations (NARX open network) for the Multi-year DSM2 Simulation
ANN Turbidity (ntu) = $\Phi 1 + \Phi 2 \cdot \text{DSM2 turbidity (ntu)}$

Location	Daily			Monthly		
	$\Phi 2$	$\Phi 1$	R^2	$\Phi 2$	$\Phi 1$	R^2
West Delta						
Sacramento River @ Rio Vista	1.0039	0.1072	0.9614	1.0292	-1.1154	0.9906
Sacramento River @ Decker Island	1.0019	0.0276	0.9623	1.0193	-0.8359	0.9983
SJR @ Jersey Point	0.9731	0.5846	0.9679	0.9812	0.5199	0.9974
Central Delta						
SJR @ Prisoner's Point	1.0096	-0.052	0.9655	1.022	-0.1598	0.9971
Old River @ Holland	0.9992	0.0618	0.9915	0.9995	0.1584	0.9992
Old River @ Quimby	1.0110	-0.0301	0.966	1.0185	-0.0715	0.997
Old River @ Bacon	0.978	0.2097	0.9774	1.0005	0.2096	0.997
Middle River @ Holt	1.0024	0.0155	0.986	1.0074	-0.0005	0.9997
Middle River @ Bacon Island	0.9521	0.0276	0.9118	0.9957	0.0614	0.9902
Turner Cut @ Holt	1.0071	0.038	0.9515	1.0563	-0.0821	0.9799
South-Southeast Delta						
Old River @ HWY4	0.9848	0.2293	0.9207	0.9957	0.3175	0.9921
Old River @ Clifton Court Intake	0.9483	0.5897	0.8864	1.0036	0.3922	0.9899
Victoria Canal	0.9481	0.254	0.9062	1.0055	-0.062	0.9947
Middle River @ Union Point	0.9762	0.1741	0.9258	1.0212	-0.1191	0.9945
Grant Line Canal @ Tracy	0.8915	1.5159	0.8853	0.9569	0.3999	0.9951
SJR @ Garwood	0.8511	1.3097	0.8064	0.9451	0.4658	0.9894

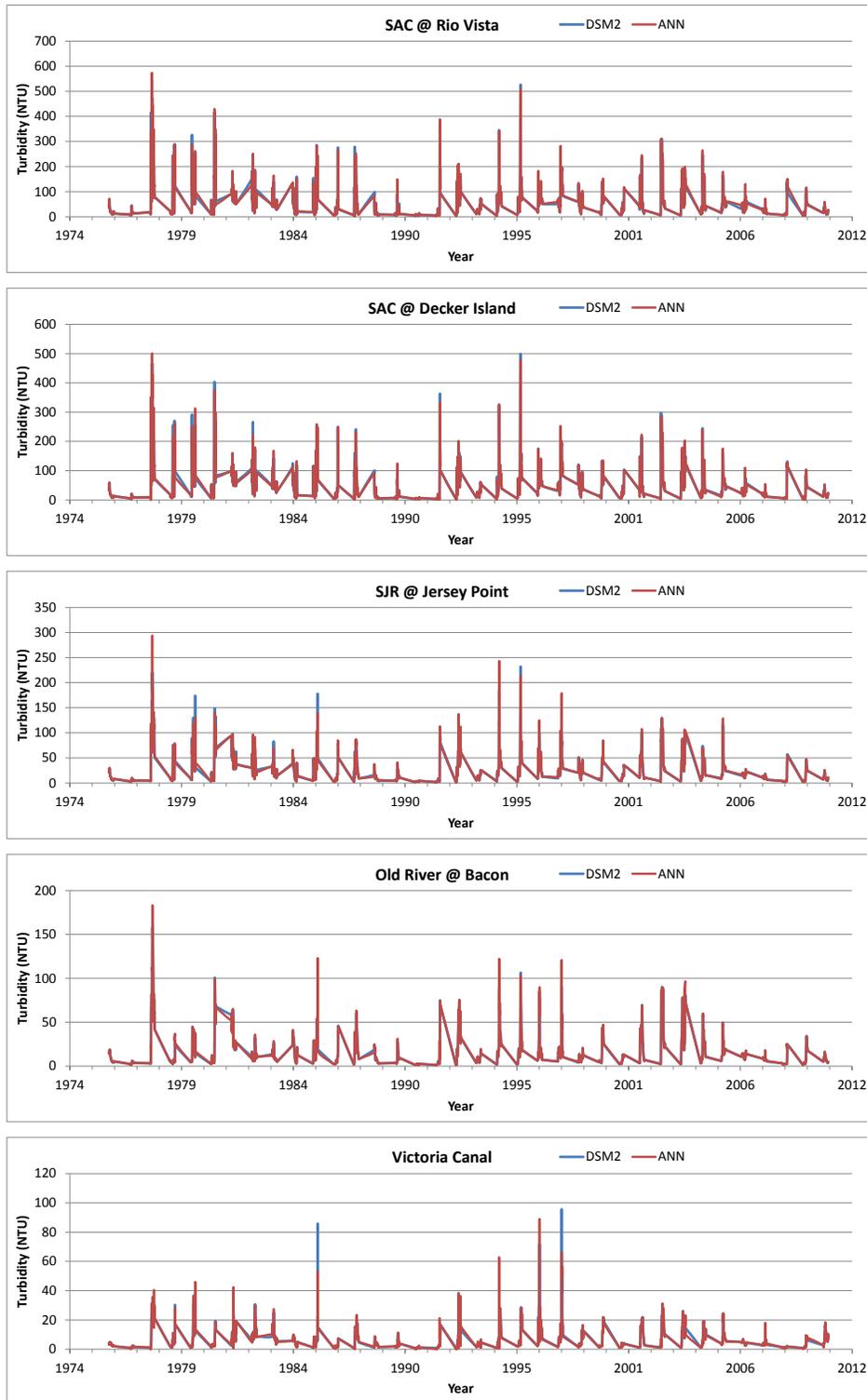


Figure 3-8 Comparison of ANN (NARX) and DSM2 simulation for the wet seasons of 1975- 2011 at representative locations. The Dec-Feb months are concatenated.

3.7 ANN FORECAST FOR WET SEASON OF 2012/2013

The trained ANN network was used to forecast turbidity levels within the Delta for storm events during the wet season of 2012/2013, thus applying the ANN to conditions that had heretofore not been part of the training, directly or through DSM2 calibration. The observed Delta hydrology (flow at Freeport, east side streams and OMR flow) and turbidity at boundary locations (north Delta, east side streams and Vernalis) and WARMF predictions at these locations were used in the forecast. The ANN predictions for the full wet season up to date using the actual hydrology and turbidity data were compared to the observed data from CDEC and are presented here (Figure 3-9 to Figure 3-12). The observed data are shown as reported on the CDEC website; no effort was made to clean the data to remove outliers or unusual values. The NARX network was trained using the open network. In the forecast mode, the trained NARX networks were converted to closed networks and used for developing forecasts.

The results for the FFW networks (Figure 3-9 and Figure 3-10) showed good agreement with CDEC data at Rio Vista and Decker Island, however the ANN showed some over-predictions in peaks of turbidity and faster decreases in turbidity than the observed data at a number of locations in the Central and South Delta. The ANN predictions also showed some under-predictions at a number of locations in the south Delta.

The results for the NARX closedloop networks (Figure 3-11 and Figure 3-12) generally showed a similar pattern to the FFW network predictions, although with lower variation. The NARX predictions showed a similar trend of over-predicting peaks and faster decline in turbidity after storm at a number of locations in the Central and South Delta and under-predictions of turbidity at a number of South Delta locations.

The differences between the ANN forecasts and observed turbidity values were closely associated with DSM2 simulations of turbidity within the Delta. The discrepancies that appear in the ANN simulations are similar to those seen in the DSM2 calibration. A comparison of DSM2 calibration to the observed CDEC data for a previous time period (2008-2011) suggested similar issues, including: 1) some over-predictions in peak turbidity and faster decline after storms at a number of central-south Delta locations; and 2) under-predictions at south-Delta locations. To illustrate this, values are shown Figure 3-13 to Figure 3-17 at representative stations: Rio Vista (north Delta), Decker Island (north Delta), Prisoner's Point (central Delta), Old River Bacon (central Delta) and Victoria Canal (south Delta). As shown in Figure 3-13, DSM2 showed over-predictions in peak turbidity at Rio Vista for certain time periods, a pattern that is similar to the ANN predictions. The Decker island station showed reasonable matches with peak turbidity, but more rapid declines in the model compared to the data (Figure 3-14). The comparison at Prisoner's Point suggested over-predictions in peak turbidity and faster declines in turbidity after peaks than the observed data (Figure 3-15). This pattern is also evident in DSM2 simulations at other Delta locations. The comparison at Old River at Bacon and

Victoria Canal represent general under-predictions in turbidity at south Delta locations by DSM2 (Figure 3-16 and Figure 3-17).

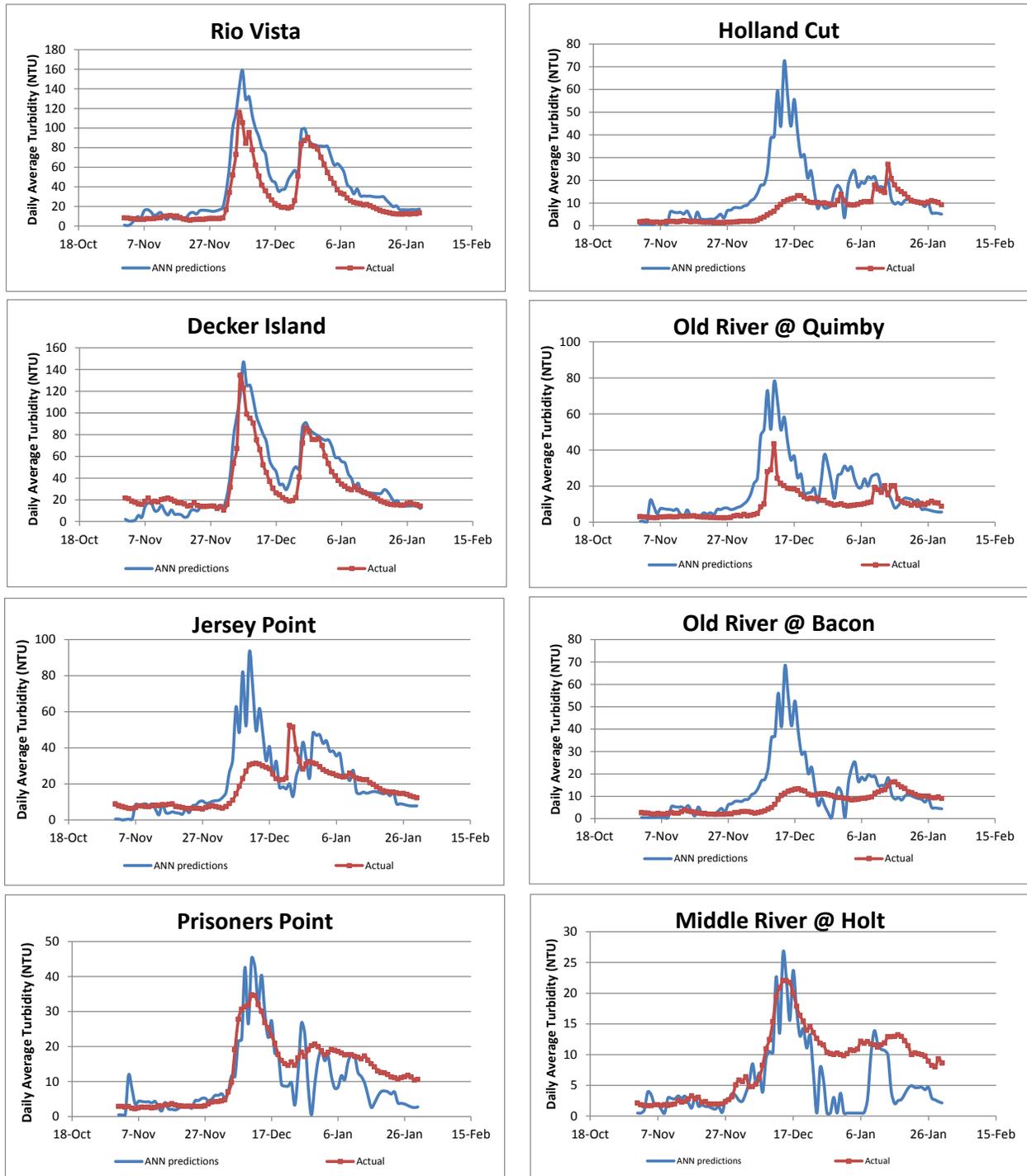


Figure 3-9 Comparison of ANN FFW model forecast and actual turbidity data from CDEC at locations within the Delta for the wet season of 2013

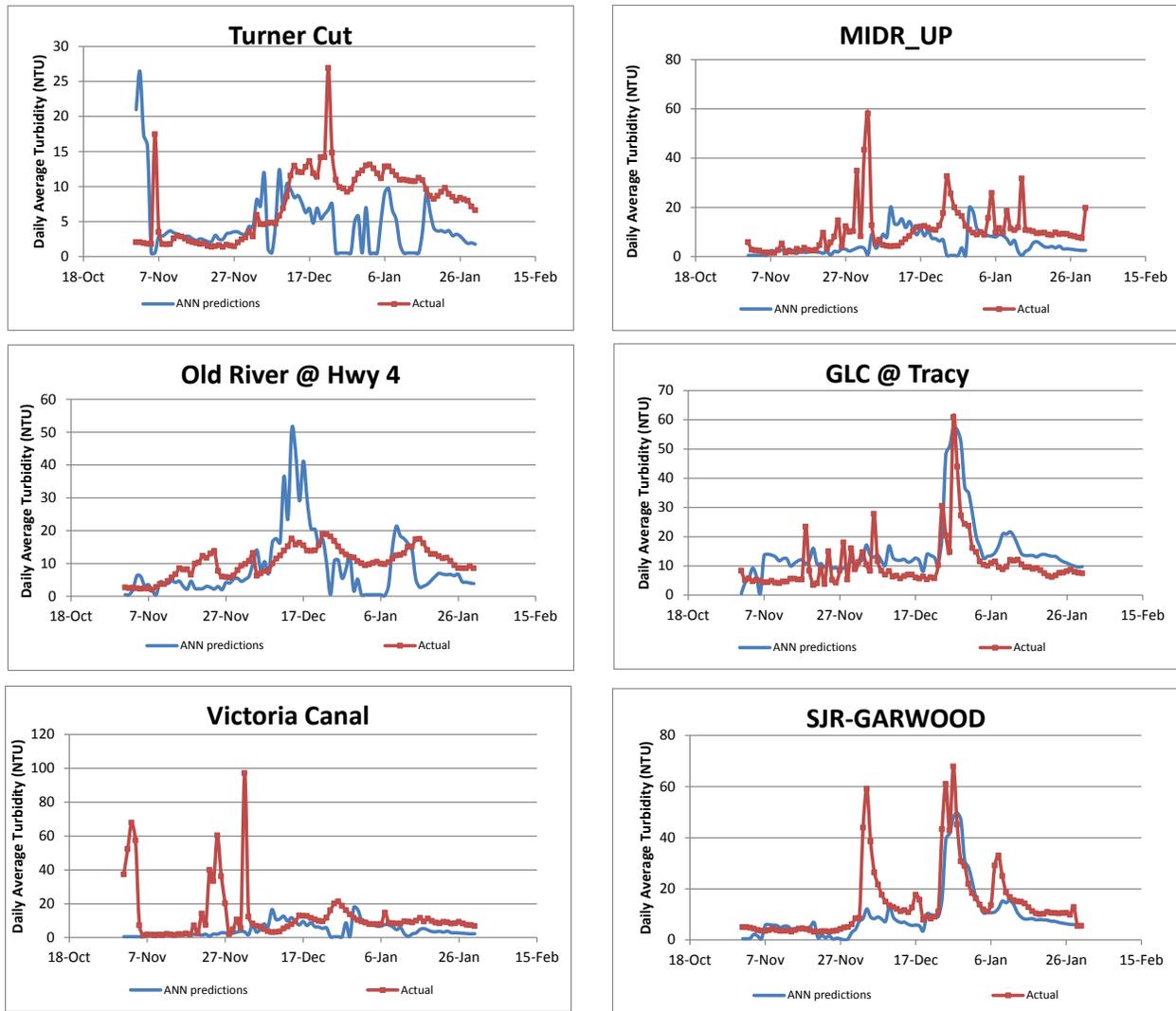


Figure 3-10 Comparison of ANN FFW model forecast and actual turbidity data from CDEC at locations within the Delta for the wet season of 2013

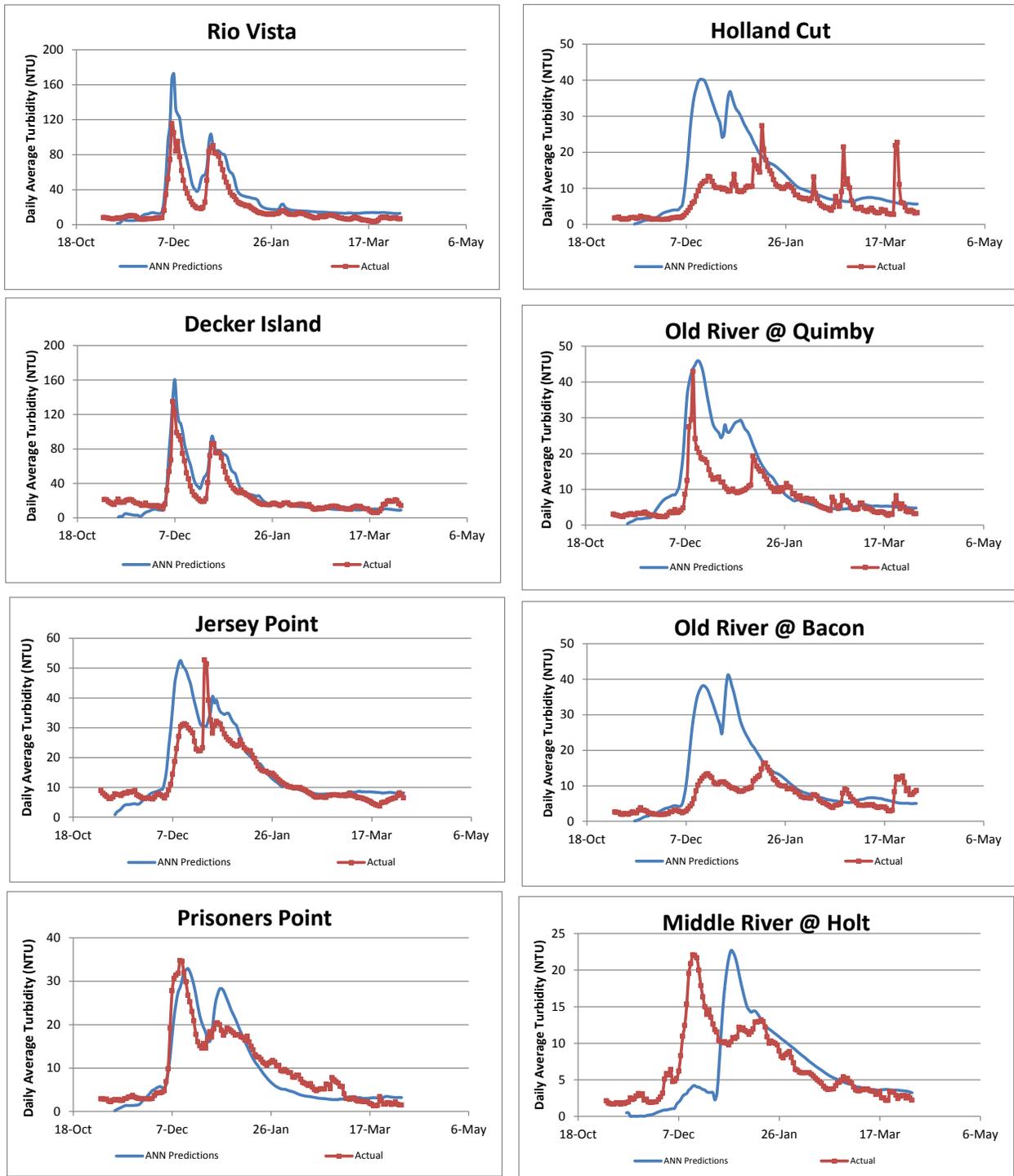


Figure 3-11 Comparison of ANN NARX closedloop model forecast and actual turbidity data from CDEC at locations within the Delta for the wet season of 2013

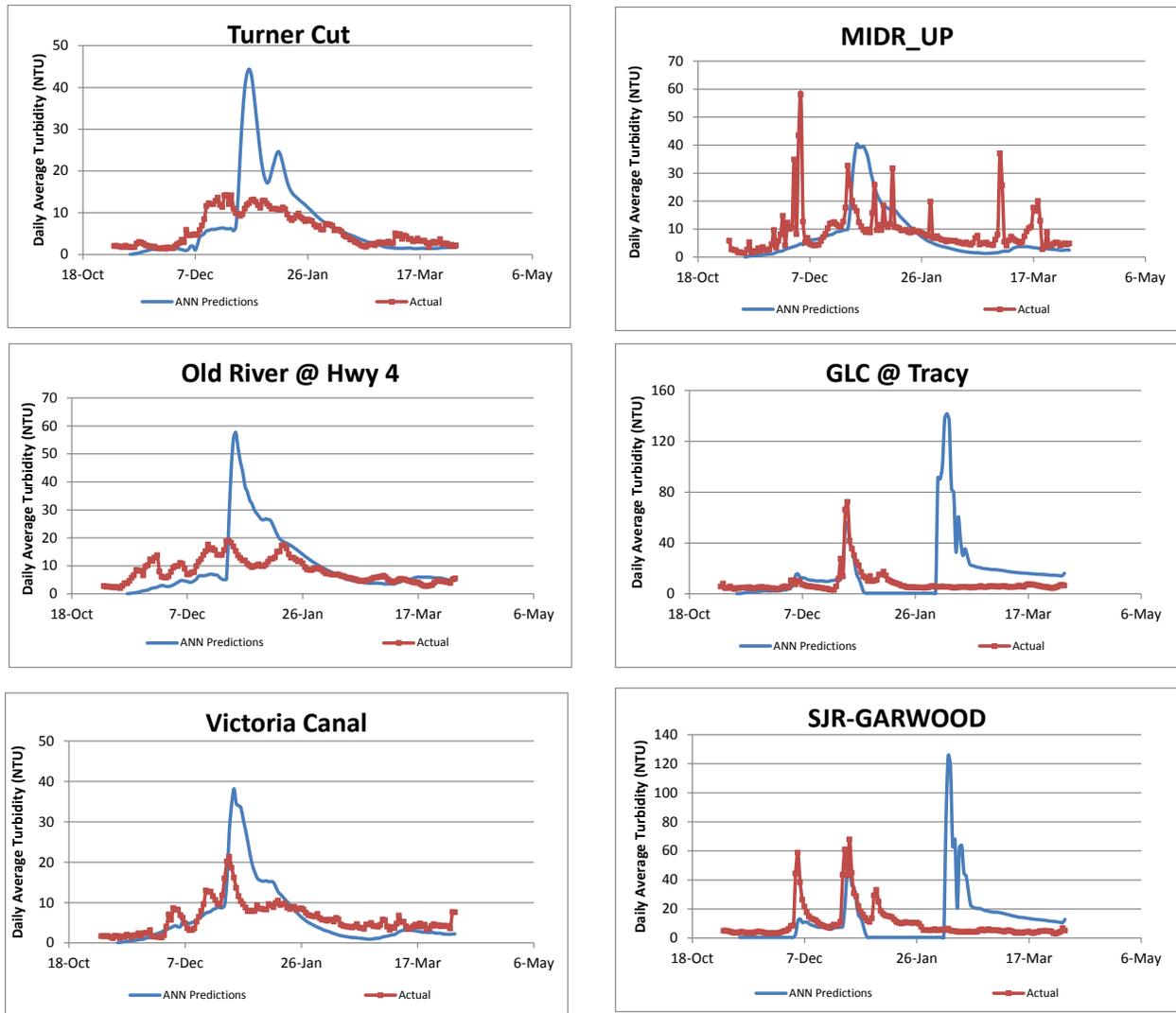


Figure 3-12 Comparison of ANN NARX closedloop model forecast and actual turbidity data from CDEC at locations within the Delta for the wet season of 2013

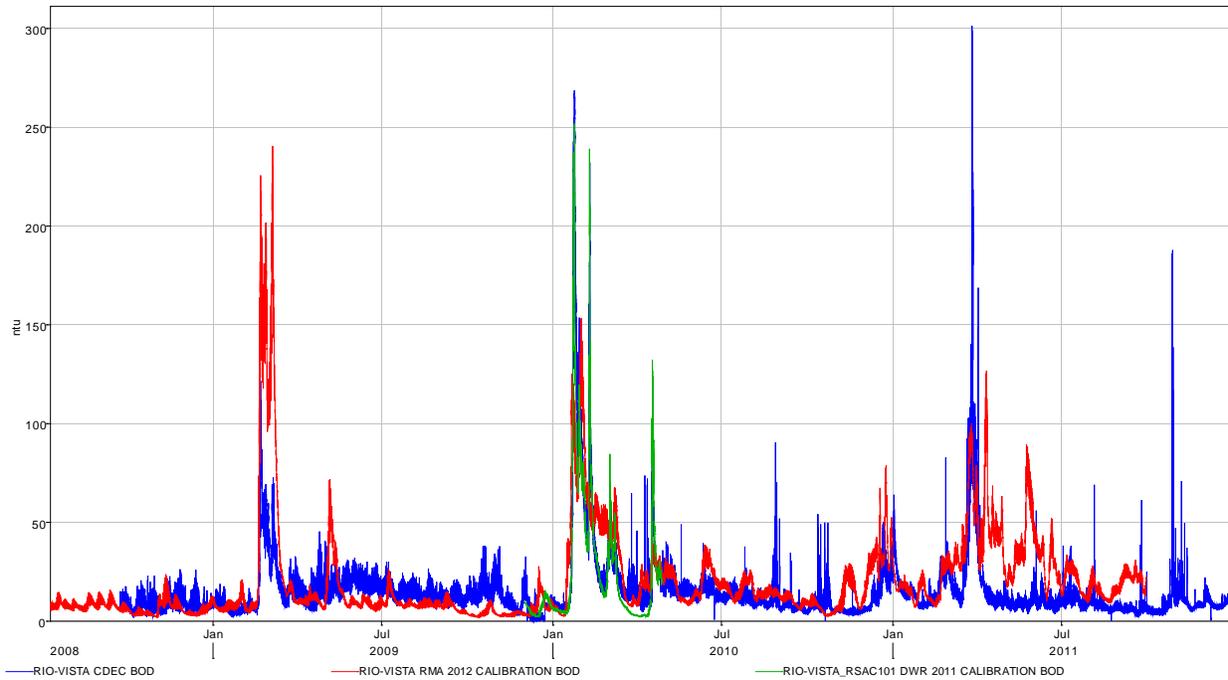


Figure 3-13 Comparison of DSM2 calibration to observed data from CDEC at Rio Vista. (Blue: CDEC data; red: RMA calibration; green: DWR 2011 calibration)

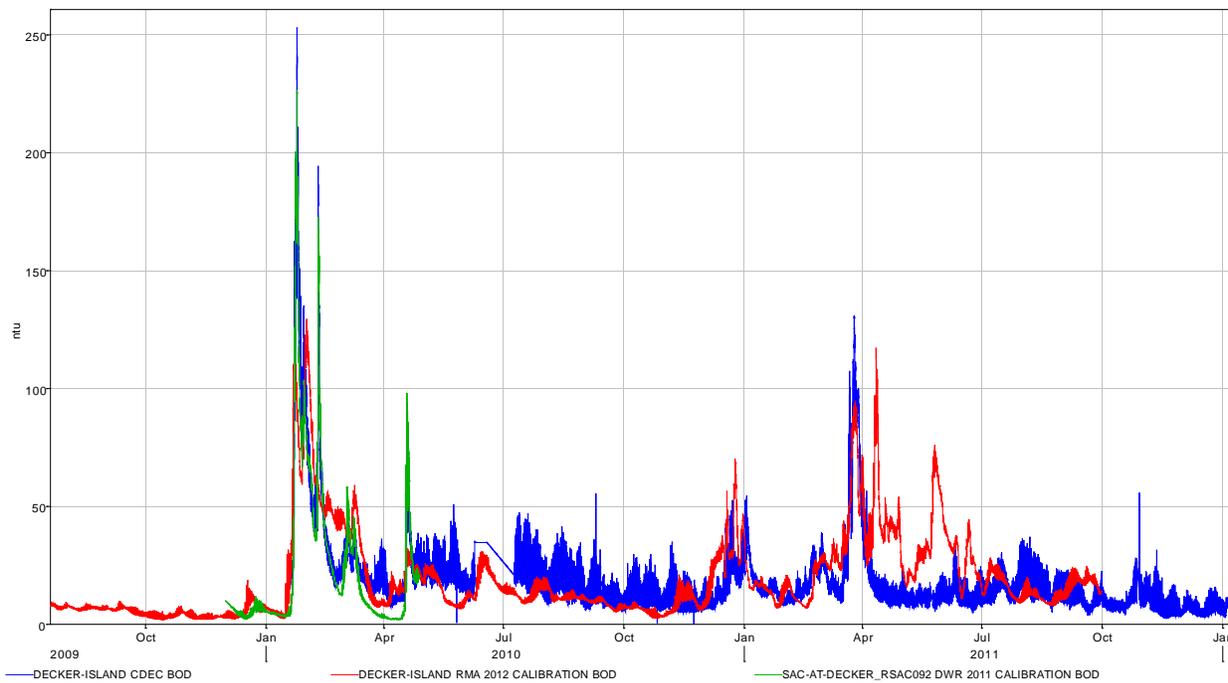


Figure 3-14 Comparison of DSM2 calibration to observed data from CDEC at Decker Island. (Blue: CDEC data; red: RMA calibration; green: DWR 2011 calibration)

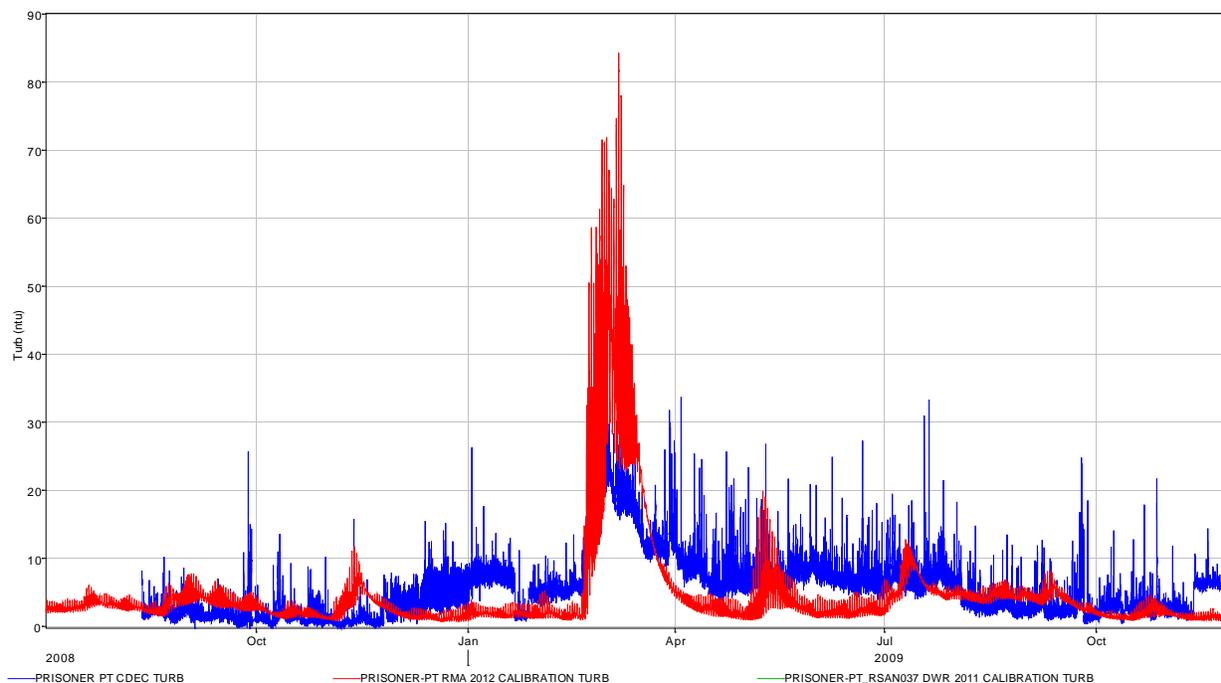


Figure 3-15 Comparison of DSM2 calibration to observed data from CDEC at Prisoner's Point. (Blue: CDEC data; red: RMA calibration)

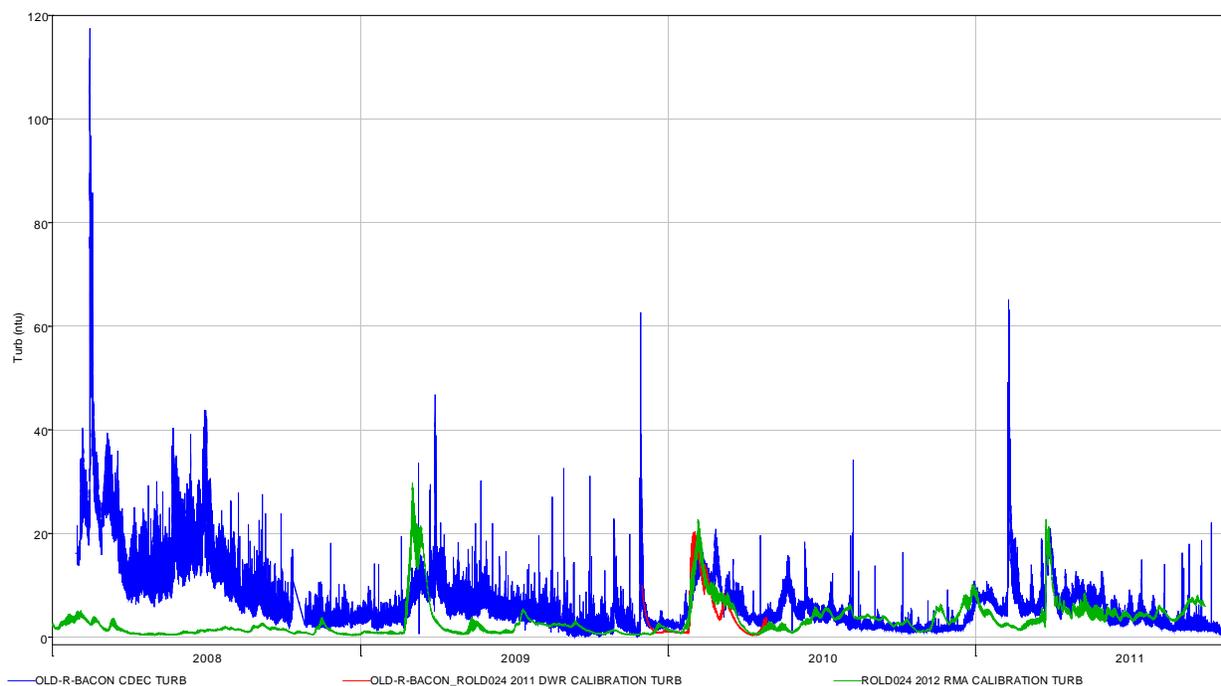


Figure 3-16 Comparison of DSM2 calibration to observed data from CDEC at Old River Bacon. (Blue: CDEC data; red: RMA calibration; green: DWR 2011 calibration)

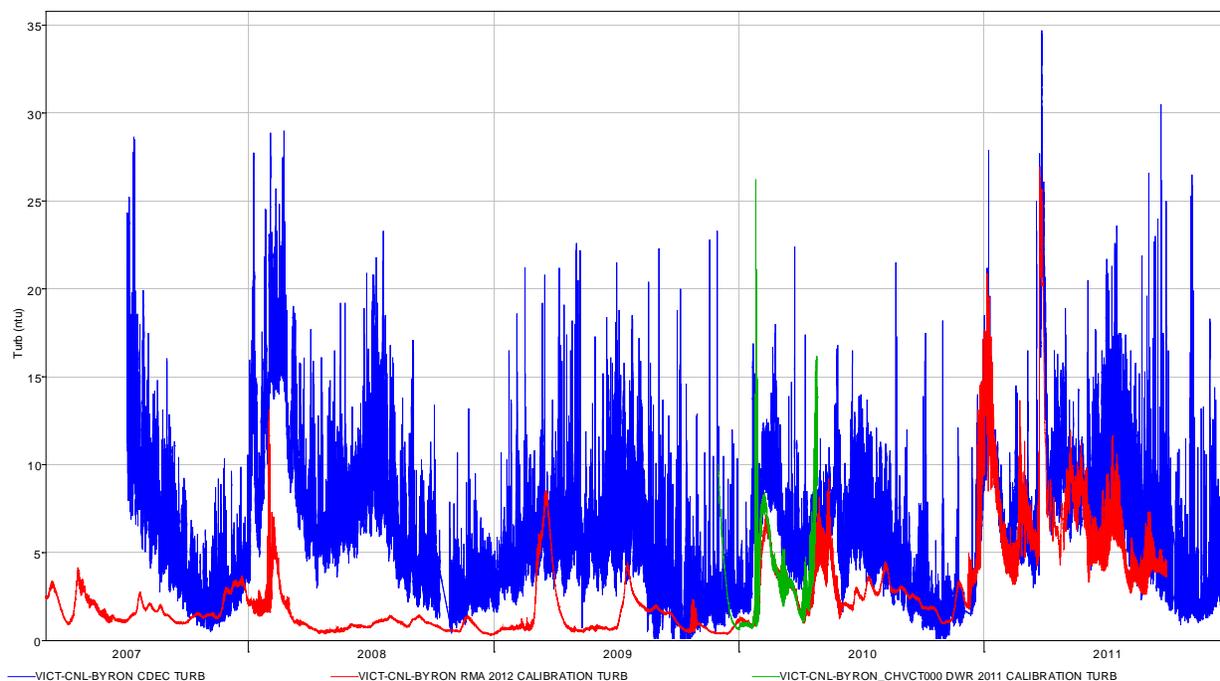


Figure 3-17 Comparison of DSM2 calibration to observed data from CDEC at Victoria Canal. (Blue: CDEC data; red: RMA calibration; green: DWR 2011 calibration)

These points can be further demonstrated through comparison of ANN NARX network results for the same time period and boundary conditions to DSM2 simulations (Figure 3-18 to Figure 3-22). The results suggest that ANN results closely follow DSM2 simulations which sometimes diverge from CDEC values at certain locations (as previously shown in Figure 3-13 to Figure 3-17). The discrepancy shown at these representative stations suggests that additional calibration of DSM2 on Delta turbidity will be beneficial to the overall goal of forecasting in the Delta.

Additional confirmation of this behavior was noted in independent DSM2 simulations performed by DWR (Bryant Giorgi, personal communication, February 11, 2013), where DSM2 output was compared to CDEC data for the wet season of 2012/2013. Plots at a representative set of stations from the DWR analysis are shown in Figure 3-23 through Figure 3-28. For the stations shown, the DSM2 results generally showed higher peaks and faster decline in turbidity after the storm, and under-predictions at South Delta locations (e.g. Victoria Canal, Old River at Highway 4). This pattern is very similar to what was noted in the ANN outputs that were trained to calibrated DSM2 data, thus supporting the need for additional calibration at some locations.

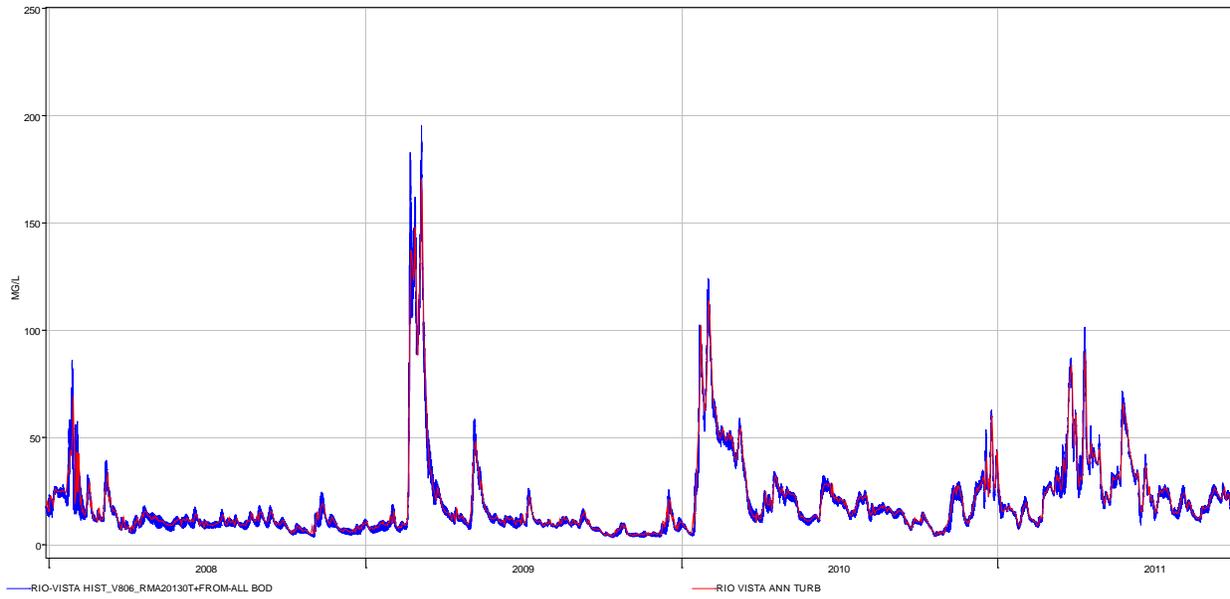


Figure 3-18 Comparison of ANN and DSM2 simulations at Rio Vista for 2008-2011.

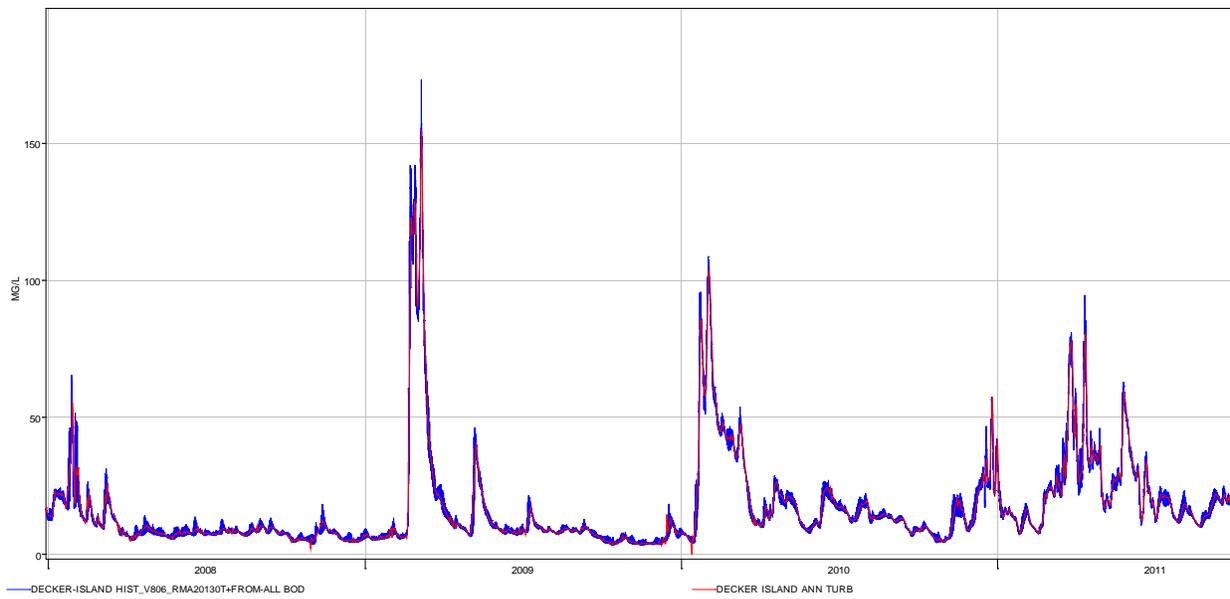


Figure 3-19 Comparison of ANN and DSM2 simulations at Decker Island for 2008-2011.

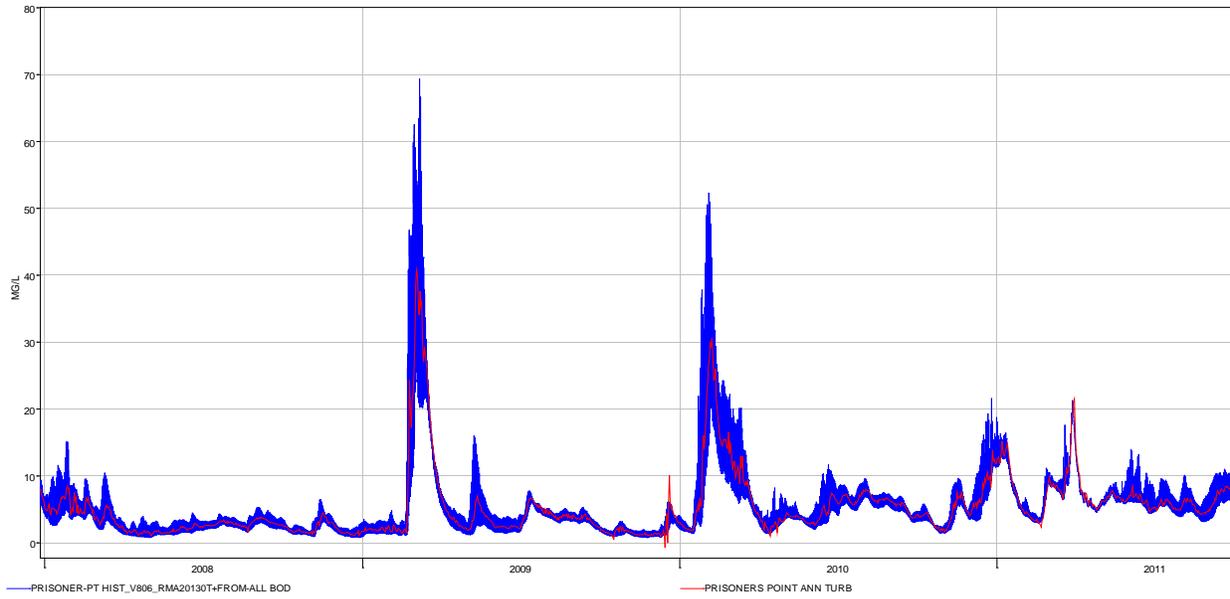


Figure 3-20 Comparison of ANN and DSM2 simulations at Prisoner's Point for 2008-2011.

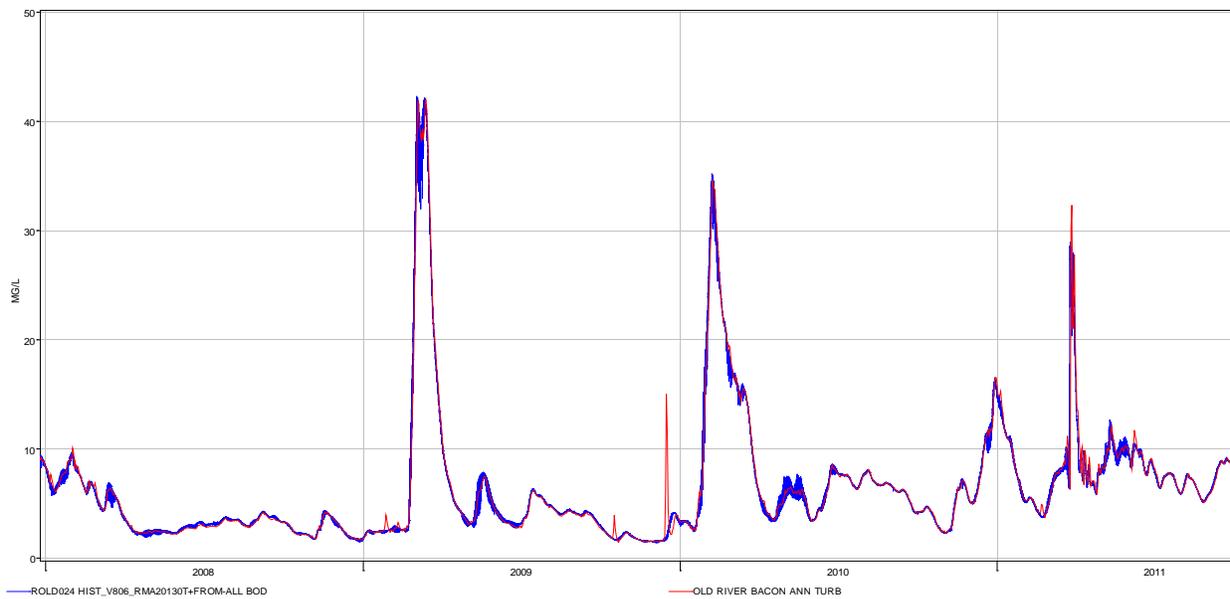


Figure 3-21 Comparison of ANN and DSM2 simulations at Old River Bacon for 2008-2011.

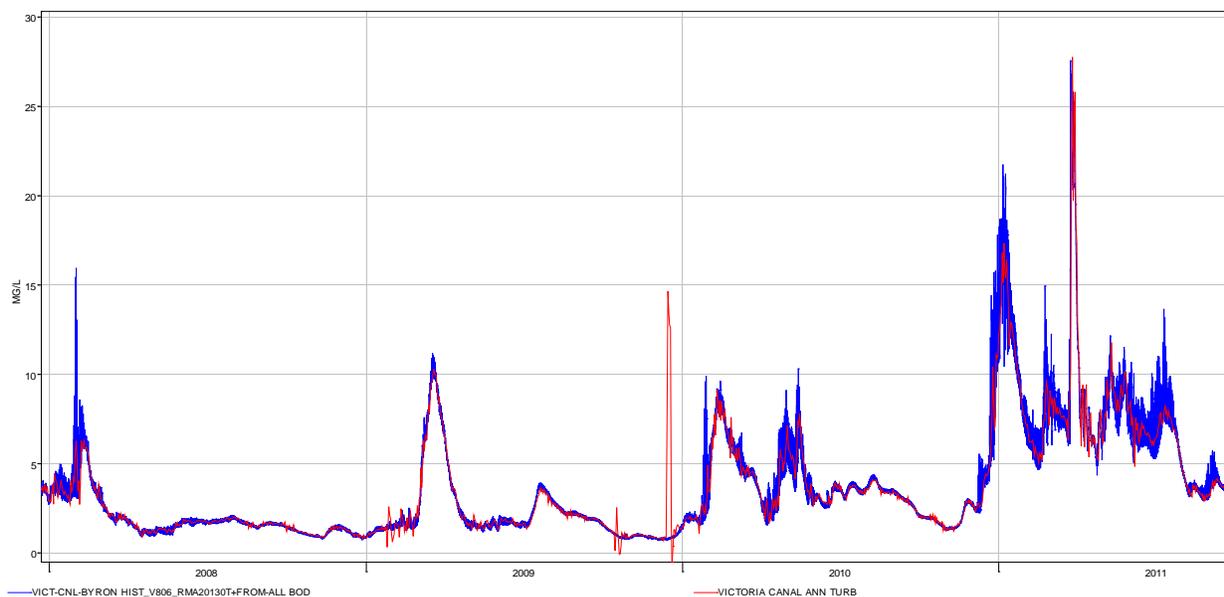


Figure 3-22 Comparison of ANN and DSM2 simulations at Victoria Canal for 2008-2011.

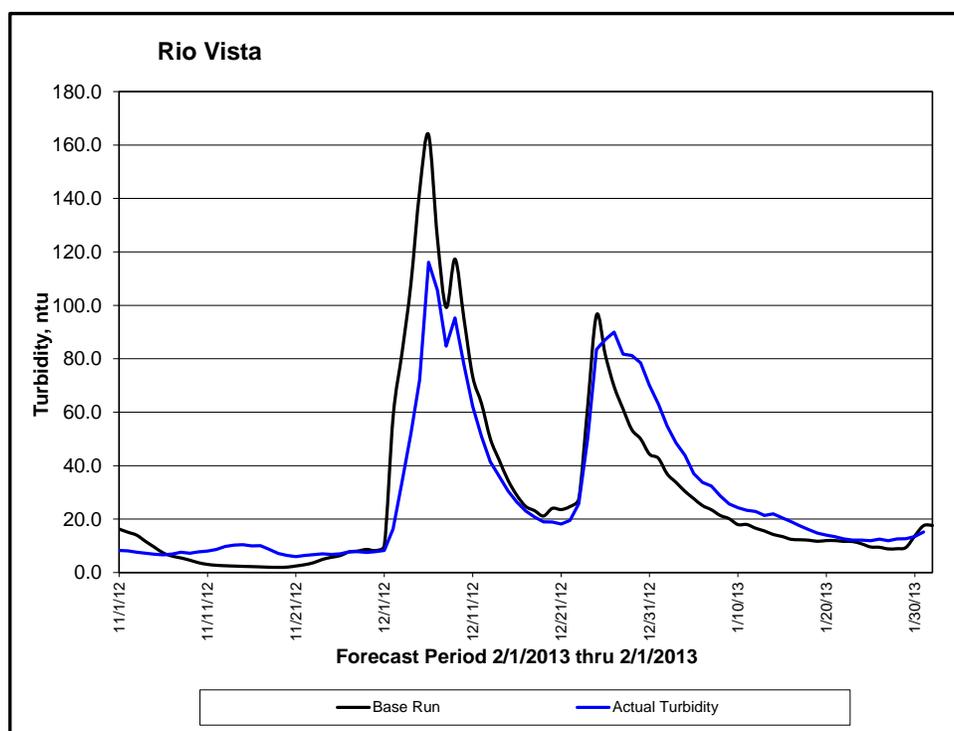


Figure 3-23 DSM2 simulations at Rio Vista (base run) compared to CDEC data for the wet season of 2012-13 (actual turbidity). DSM2 runs performed by DWR.

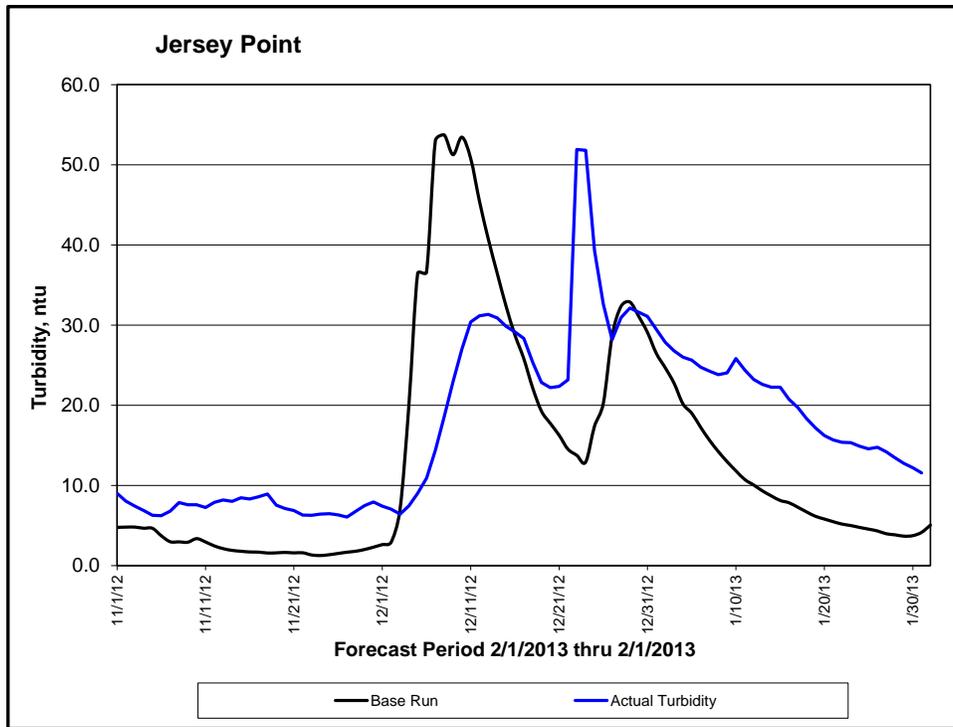


Figure 3-24 DSM2 simulations at Jersey Point (base run) compared to CDEC data for the wet season of 2012-13 (actual turbidity). DSM2 runs performed by DWR.

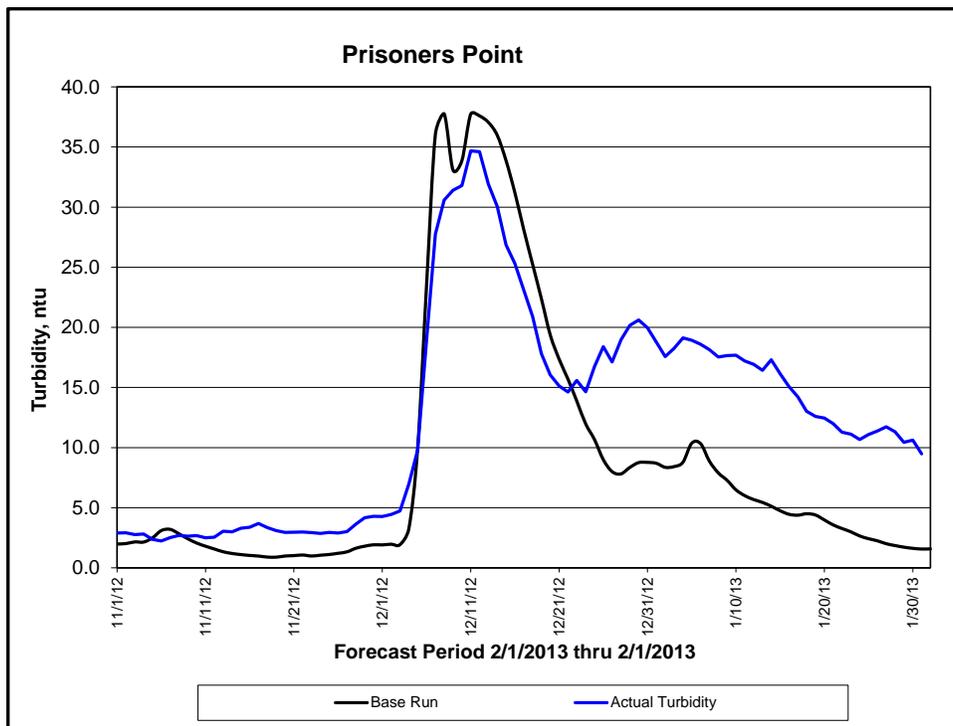


Figure 3-25 DSM2 simulations at Prisoner's Point (base run) compared to CDEC data for the wet season of 2012-13 (actual turbidity). DSM2 runs performed by DWR.

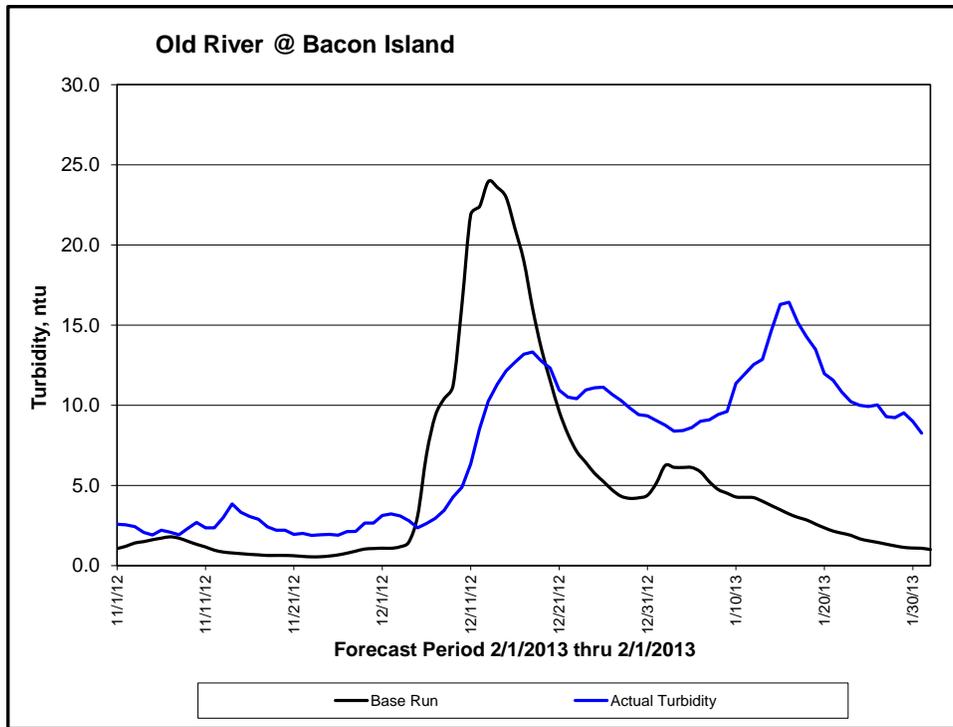


Figure 3-26 DSM2 simulations at Old River at Bacon Island (base run) compared to CDEC data for the wet season of 2012-13 (actual turbidity). DSM2 runs performed by DWR.

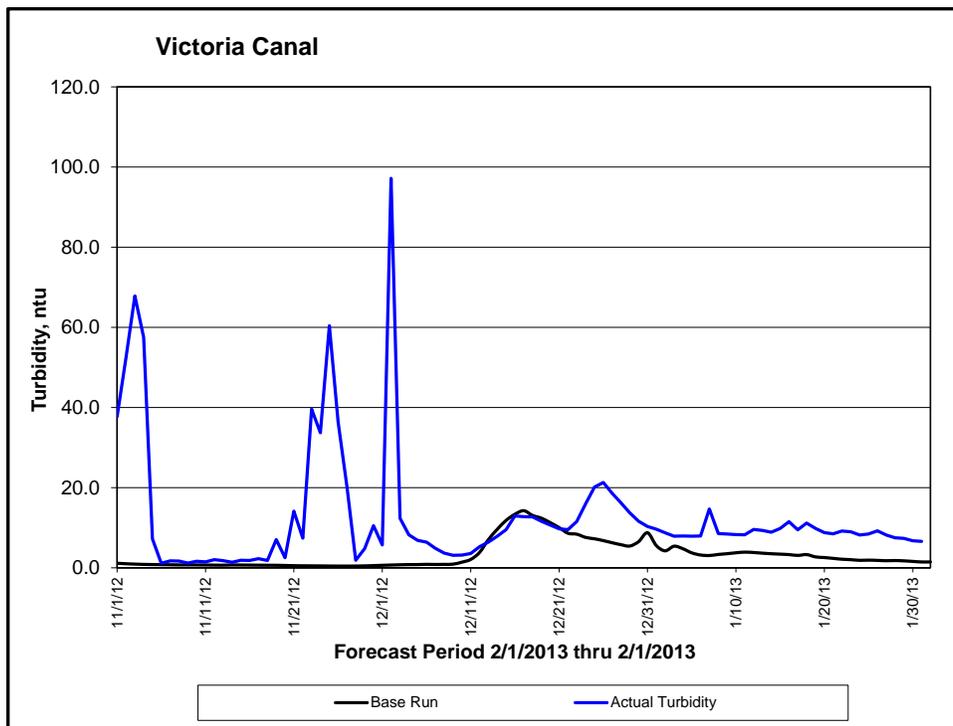


Figure 3-27 DSM2 simulations at Victoria Canal (base run) compared to CDEC data for the wet season of 2012-13 (actual turbidity). DSM2 runs performed by DWR.

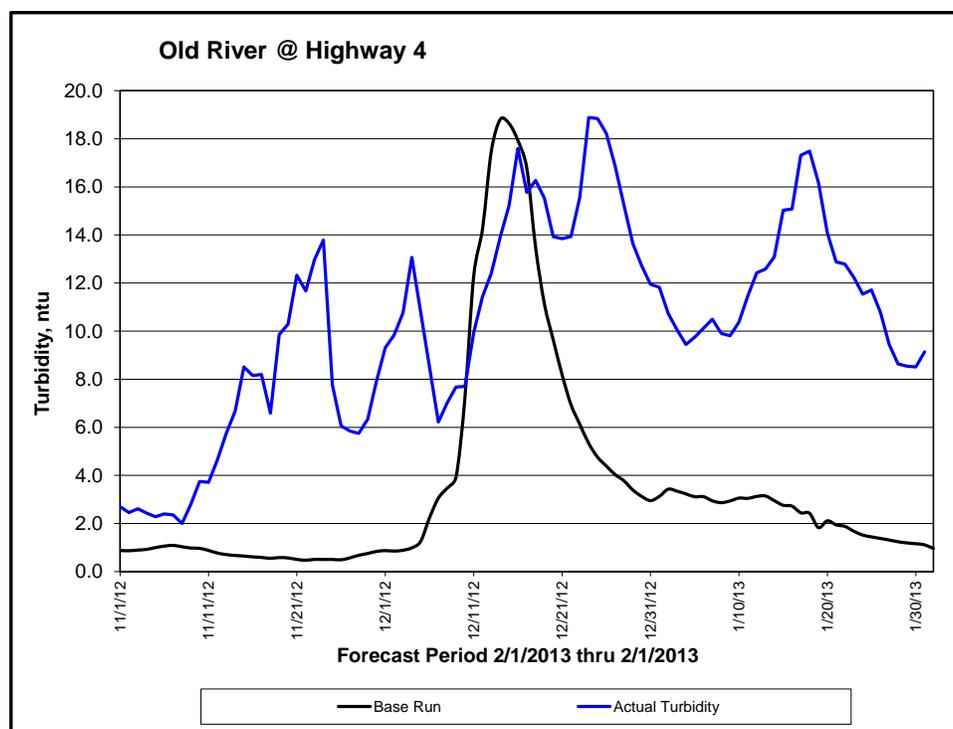


Figure 3-28 DSM2 simulations at Old River at Highway 4 (base run) compared to CDEC data for the wet season of 2012-13 (actual turbidity). DSM2 runs performed by DWR.

3.8 USE OF OMR FLOW MODIFICATION TO CONTROL TURBIDITY

To avoid triggering the USFWS “first flush” Reasonable and Prudent Action (RPA, Component 1, Action 1), operations in the Delta must meet a turbidity threshold of 12 NTU at three compliance stations: Holland Cut at Bethel Island (HOL), Victoria Canal (VCU), and Prisoner’s Point (PPT), during the period approximated by the months of December, January and February, roughly corresponding to the Delta smelt spawning period. This section examines the use of the feedforward ANN to evaluate turbidity management through control of the OMR flow by reduction of the Delta exports. The autoregressive NARX approach is not appropriate for this analysis because the goal is to modify turbidity at individual stations, values which may become part of the autoregressive input.

The ANN model (feedforward network) was first run using the historical inputs of flow and turbidity at the Delta boundaries. The ANN modeled and the DSM-2 calculated turbidities across three compliance stations, as well as the minimum turbidity for the three stations in shown in Figure 3-29. There is good agreement between the two modeling approaches over the entire period, but there are situations where the ANN over- or under-predicts the DSM2 turbidity.

For the historical time period of 1975-2011, the ANN model output was used to calculate events where turbidity exceedance could have occurred during December, January and February. The 2012-13 season was addressed separately, as discussed below, because

observed turbidity data were available for the high turbidity periods during this season. In all cases, a non-compliance event was defined as the minimum turbidity at three compliance stations exceeding the threshold of 12.0 NTU by 0.1 NTU for three consecutive days. This analysis also included the month of November initially, but November months were not found to contribute to the occurrence of turbidity events over the 1975-2011 period. For the remaining analysis presented below, we focus only on December, January and February events.

3.8.1 MULTI-YEAR ANALYSIS (1975-2011)

Analysis of exceedance using the ANN results showed that 37 modeled exceedance events in 20 distinct water years occurred over 1975-2011 (Table 3-4). The events are related to the water year classification as follows:

- Critically dry years: 1988, 1992 (two years)
- Below normal and dry years: 1979, 2002, 2004 (three years)
- Above normal and wet years: 1978, 1980, 1982, 1983, 1984, 1986, 1993, 1995, 1996, 1997, 1998, 2000, 2003, 2005, 2006 (fifteen years)

The summary above clearly shows that turbidity exceedance events are more frequent in wetter years that are more likely to be associated with high flows and turbidities at the Delta boundaries. However, individual storm events may lead to turbidity exceedances even in years nominally classified as dry as is seen in the exceedances associated with five below normal, dry, and critically dry years.

Given this modeled history of turbidity exceedance, we then adjusted OMR flows in 500 cfs increments, until the compliance criteria were met or the greatest controllable OMR change was reached. The greatest controllable OMR flow for any given day was computed by using a correlation between OMR flow and San Joaquin River flow and South Delta exports (Hutton, 2008), and by setting the exports to zero. The changes in OMR flow were initiated 7 days ahead of the non-compliance event which is the time lag in the ANN turbidity model. An example of the turbidity at a specific location (Victoria Canal) is shown using the original OMR flow and the modified OMR flow in Figure 3-30. In this example, the turbidity at this station is slightly above 12 NTU and the allowable change in OMR flow leads to a decrease below this criterion.

For the overall turbidity control exercise, the modified OMR flow was calculated for each event during which control was achieved. Of the 37 modeled events that were identified, control was possible in only 9 events, with control being defined as minimum turbidity being reduced below 12 NTU for all days of the exceedance event. In terms of smelt seasons, 20 were modeled and only 3 were controlled. Table 3-4 shows the summary of events identified by the ANN model for the period of 1975-2011, and the calculated changes in OMR flow. The total required flow changes required were calculated in terms

of cost of export in TAF, for only those events where turbidity control was possible. For context, mean and maximum values of the other five inputs to the ANN model are also summarized in Table 3-4: North Delta turbidity, East side turbidity, Vernalis turbidity, North Delta flow, and East side stream flow. Given the large range in these inputs and day-to-day variation during storm events, these values are summarized and mean and maximum across the season of interest (December, January, and February), and not just the days associated with the event.

The following explains the conditions under which turbidity control was either possible or not possible using the OMR flow as a controlling variable.

- Achievable events (1, 11, 25, 26, and 29, 31-34) are associated with relatively low mean North Delta flows (in approximately the 40-60,000 cfs range), with OMR flows in approximately the -7,000 to -9,000 cfs range, and mean Vernalis flows less than 2,700 cfs. With one exception (wet season 2000), mean East Side flows associated with controlled events were less than 1,400 cfs. The controllable events were spaced among six water years, of which one was critically dry (1988), one was dry (2002), one was below normal (2004) three were above normal (1978, 2000, 2003). For years where control was possible, OMR flow modification ranged from 1,400 to 4,600 cfs. None of the wet year events were controlled.
- Some events are not-achievable due to generally high mean north Delta flow (>100,000 cfs) in the season, and particularly during or before the event (e.g., events 4-10, 17, 19, 20-24, and 37). Events 4 and 5 are characterized by a seasonal mean north Delta flow of 120,000 cfs in 1980. Event 6 and 7 are characterized by a high seasonal mean north Delta flow of 127,200 cfs in 1982. Event 8 has a high seasonal mean north Delta flow of 123,100 cfs in 1983. Event 9 has a high seasonal mean north Delta flow of 190,000 cfs. Event 10 has a high seasonal mean north Delta flow of 158,000 cfs. Events 19-22 of 1997 have a seasonal mean north Delta flow of 130,300 cfs. Events 23-24 of 1998 have a seasonal mean north Delta flow of 129,800 cfs. Event 37 of 2006 has a seasonal mean north Delta flow of 193,700 cfs.
- For some events although the seasonal mean north Delta flow is not high, the event is characterized by high north Delta flow before or during the event (e.g., event 2, 18, and 27). Also, for event 30, the flows are not unusually high, but the mean North Delta turbidity was high (190 NTU mean, 436 NTU maximum).
- The rest of the non-achievable events are mostly due to increased turbidity under positive OMR (e.g. event 3, 12, 13, 14, 15, 17, 28, 35, and 36). As shown in the sensitivity analysis (Figure 3-4), turbidity at Victoria Canal increased when OMR became positive. Therefore when the OMR flow is increased to become positive,

turbidity increases if the turbidity criterion was not achieved at a lower OMR value.

3.8.2 ANALYSIS FOR THE 2012-2013 WET SEASON

In addition to the 1975-2011 period discussed above, the 2012-13 wet season turbidity was analyzed using the ANN approach. This season differs from the preceding period because of the availability of observed data during a period of high turbidities. The real time turbidity sensors were placed in the Delta in 2009, but there were no turbidity events, as calculated by the ANN approach between 2009 and 2012. For this event the ANN values can also be compared with observations.

Observed turbidity values at the three compliance stations are shown in Figure 3-31. Based on a narrow definition of a non-compliance event, three days with minimum turbidity exceeding 12 NTU, the 2012-13 wet season did not result in a turbidity exceedance event, because one of the three compliance stations was below the threshold. This appears counter-intuitive because the stations appear to have high turbidities for an extended period, especially the Holland Cut and the Prisoner's Point stations. However, third station, Victoria Canal, had lower turbidities for much of the period, and therefore, there is only one day where the minimum turbidity for all three stations exceeds 12 NTU (Figure 3-32). Because we are defining an exceedance event as three days with minimum turbidity in excess of 12 NTU, this period does not strictly qualify as an exceedance event. However, because these high turbidities occurred recently, and because there is interest in this event with respect to control, it was identified for further analysis.

The ANN-calculated turbidities for the same period are presented in Figure 3-33 and show a similar, although not identical, behavior with no modeled event having occurred with the specific definition set out above (there were fewer than three days of 12 NTU minimum turbidity). The trained ANN was then used to explore changes in turbidity through changes in OMR flow. For this season, the allowable range of OMR flow control, obtained by setting exports to zero, is shown in Figure 3-34. The results of OMR flow change are presented for each of the three compliance stations in Figure 3-35. The results show that OMR flow control can be used to decrease turbidity at all stations, especially at the Holland Cut and Prisoner's Point stations that were substantially elevated, although not entirely below 12 NTU for the entire wet season.

3.8.3 SUMMARY OF TURBIDITY CONTROL USING OMR FLOWS

The above approach thus allows an exploration of conditions under which high turbidity events occur, and the subset of events which can be controlled, given our best understanding of the turbidity transport processes through the DSM2 model (and emulated through the ANN model). Because of the rapid change of boundary conditions during storm events (both flows and turbidities), calculated turbidities at compliance stations also change relatively rapidly, and need to be evaluated in the carefully given the exact definition of exceedance (>12.1 NTU). It is possible that such a numeric target

may be too precise given the available modeling knowledge on turbidity, and more appropriate targets may consider a range of turbidity (before and after OMR control) rather than one numeric value. Also, the finding that many events are not controllable through the OMR flow is of importance to the Delta operations, and needs to be investigated more fully through mechanistic modeling beyond what is presented here.

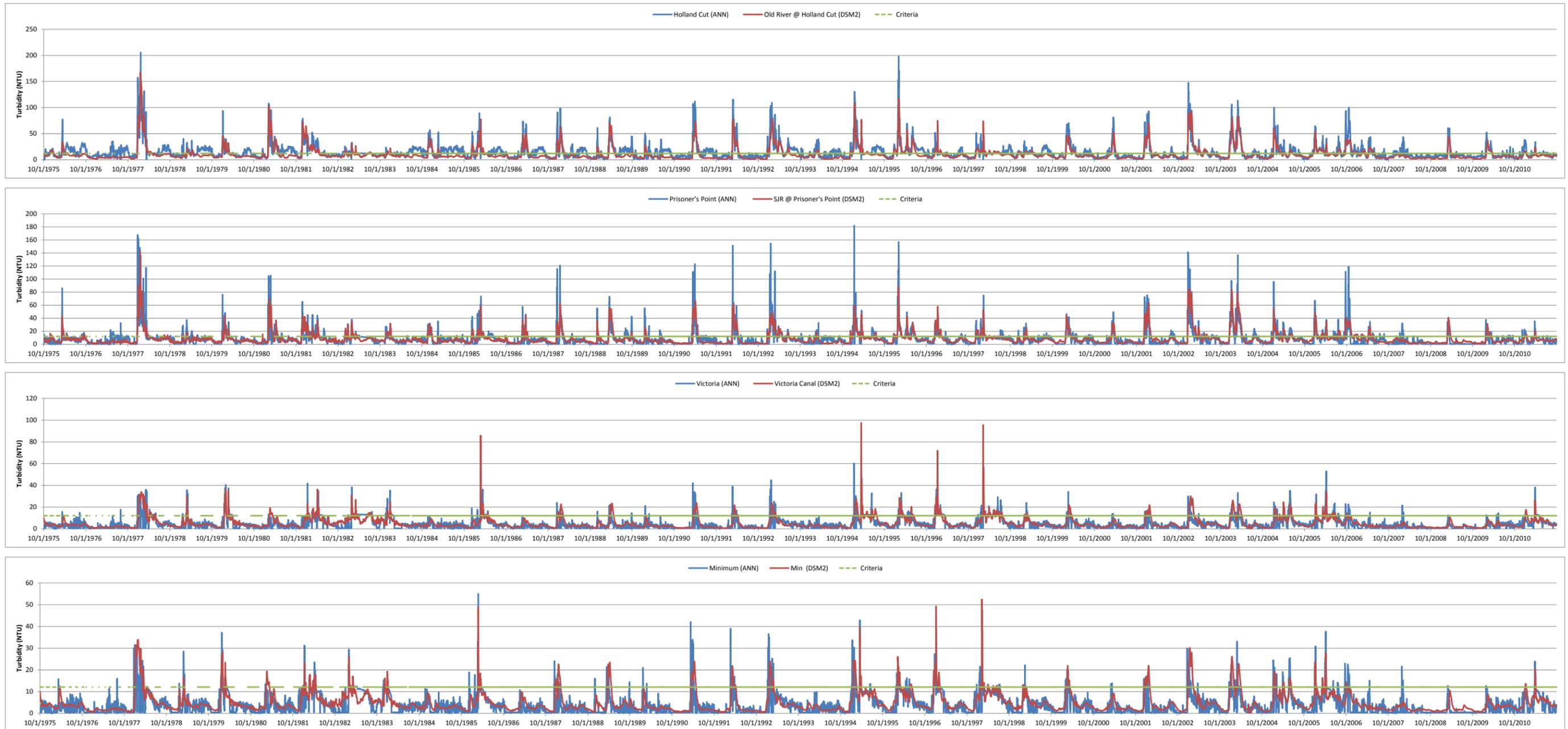


Figure 3-29 ANN simulated turbidity compared to DSM2 results for the period of 1975-2011

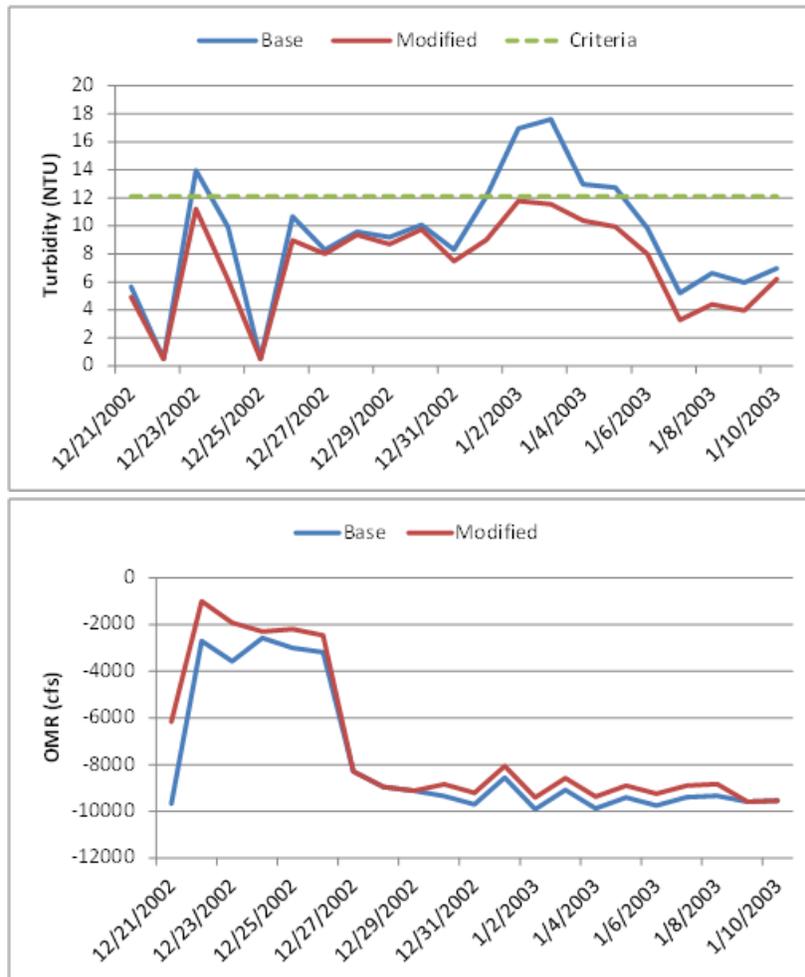


Figure 3-30 Simulated turbidity at Victoria Canal due to export modification and the corresponding OMR flow.

**Table 3-4
ANN simulated non-compliance events for the period of 1975- 2011 and the required changes in OMR.**

Event	Start date	End date	Month	Event Mean Values (cfs)					Season Mean Values					Season Maximum Values					Duration of exceedance event (days)	Non achievable days	Export cost (TAF)
				OMR final	OMR original	Allowed OMR change assuming zero export	Vernalis flow	South Delta diversions	North Delta turbidity (NTU)	East side turbidity (NTU)	Vernalis turbidity (NTU)	North Delta inflow (cfs)	East side stream flow (cfs)	North Delta turbidity (NTU)	East side turbidity (NTU)	Vernalis turbidity (NTU)	North Delta inflow (cfs)	East side stream flow (cfs)			
1	12/31/1977	1/5/1978	December	-4,000	-8,600	8,800	600	9,400	239	37	36	47,900	1,400	627	145	132	157,200	9,000	6	0	64.5
2	1/21/1978	2/4/1978	January		-7,700	9,400	3,300	9,800											15	5	
3	2/24/1979	2/28/1979	February		1,300	3,100	9,100	3,500	142	47	31	44,000	3,200	322	110	54	76,500	8,300	5	5	
4	1/20/1980	2/1/1980	January		5,500	5,800	20,900	6,300	131	36	36	120,700	7,900	321	80	84	296,200	19,900	13	13	
5	2/23/1980	2/26/1980	February		10,100	2,900	23,100	3,100											4	4	
6	1/10/1982	1/14/1982	January		-2,300	4,300	4,500	4,800	83	35	35	127,200	7,900	135	116	161	209,000	26,100	5	4	
7	2/22/1982	2/27/1982	February		-4,500	9,700	10,000	10,200											6	6	
8	1/27/1983	2/4/1983	January		3,400	9,600	23,200	10,200	116	38	31	123,100	8,700	189	67	81	235,600	17,200	9	9	
9	12/31/1983	1/5/1984	December		9,600	3,300	23,100	3,600	82	51	21	190,000	11,700	175	87	39	314,700	20,000	6	6	
10	2/23/1986	2/25/1986	February		4,800	4,600	17,600	4,900	136	56	48	158,000	9,500	282	128	172	612,300	40,600	3	3	
11	1/12/1988	1/17/1988	January	-6,800	-8,800	9,400	1,300	10,600	119	22	16	26,500	300	428	71	52	40,400	1,100	6	0	28.8
12	2/19/1992	2/21/1992	February		-5,500	7,200	3,500	8,100	216	44	73	39,600	1,200	605	95	149	49,500	3,300	3	2	
13	2/23/1992	2/25/1992	February		-7,900	8,900	2,400	10,100											3	1	
14	1/30/1993	2/4/1993	January		-7,400	8,900	3,100	9,900	138	49	52	53,100	1,800	324	144	213	126,300	7,400	6	4	
15	2/15/1993	2/18/1993	February		-8,800	10,800	3,400	11,600											4	1	
16	1/16/1995	1/24/1995	January		-9,100	11,000	4,300	12,300	156	55	79	100,200	3,100	453	200	309	238,700	12,200	9	7	
17	2/1/1996	2/4/1996	February		-3,700	6,500	5,200	6,600	207	36	42	91,600	4,300	639	100	95	180,600	10,100	4	4	
18	2/23/1996	2/25/1996	February		2,400	5,200	14,800	5,000											3	3	
19	12/18/1996	1/2/1997	December		300	6,700	14,100	7,200											16	10	
20	1/6/1997	1/12/1997	January		22,500	3,300	43,900	4,600	97	39	29	130,300	11,100	243	103	74	507,500	53,700	7	7	
21	1/28/1997	2/9/1997	January		17,600	1,300	32,000	1,100											13	13	
22	2/12/1997	2/14/1997	February		19,200	1,800	35,000	2,000											3	3	
23	1/21/1998	1/26/1998	January		900	3,400	9,400	4,000	128	44	41	129,800	5,600	370	126	165	274,000	20,300	6	6	
24	2/8/1998	2/15/1998	February		7,400	4,200	20,500	3,700											8	8	
25	2/3/2000	2/6/2000	February	-6,900	-9,200	10,300	2,700	11,600	89	44	40	89,500	3,900	185	110	136	167,000	10,700	4	0	45.6
26	2/8/2000	2/10/2000	February	-6,700	-9,100	10,000	2,200	11,200											3	0	18.8
27	2/22/2000	2/24/2000	February		-5,400	11,200	12,200	12,100											3	1	
28	12/12/2001	12/15/2001	December		-7,000	9,600	5,500	10,500	125	21	24	40,500	700	248	77	85	100,500	2,500	4	1	
29	1/15/2002	1/19/2002	January	-6,600	-8,700	9,800	2,500	11,000											5	0	44.6
30	12/25/2002	12/30/2002	December		-6,700	7,700	2,400	8,800	190	13	30	54,700	600	436	32	100	90,900	1,300	6	1	
31	1/7/2003	1/12/2003	January	-5,600	-9,100	10,100	2,000	11,200											6	0	75.4
32	12/31/2003	1/3/2004	December	-4,900	-8,500	9,200	1,700	10,400											4	0	71.4
33	1/7/2004	1/12/2004	January	-4,700	-9,200	10,200	2,000	11,500	137	22	24	61,000	900	264	79	121	159,600	4,200	6	0	80.3
34	2/11/2004	2/14/2004	February	-6,800	-8,200	8,800	1,700	9,900											4	0	26.8
35	1/5/2005	1/11/2005	January		-8,700	10,700	3,900	11,500	134	35	55	35,300	1,700	373	74	94	56,400	4,500	7	3	
36	1/16/2005	1/18/2005	January		-7,600	10,900	7,000	12,000											3	2	
37	1/4/2006	1/13/2006	January		-2,300	8,900	13,300	9,600	112	51	45	193,700	7,500	188	109	77	341,600	24,400	10	9	

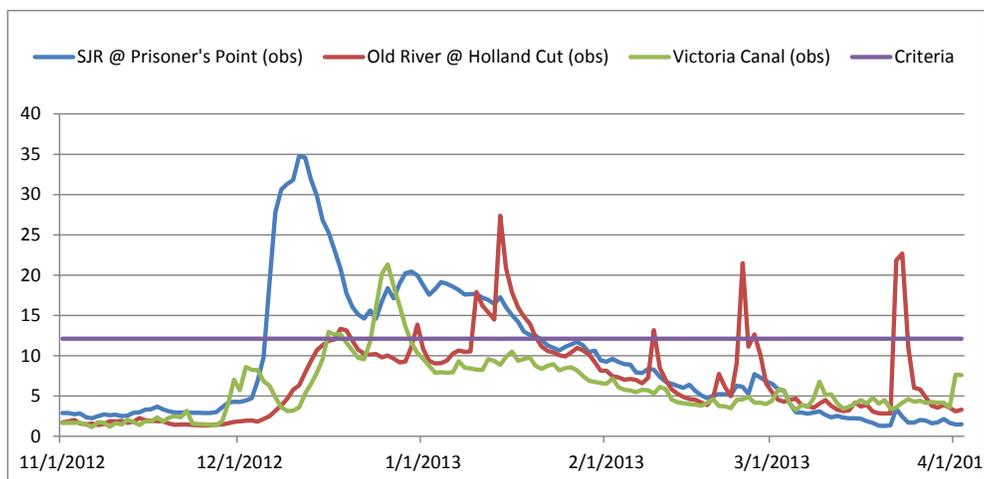


Figure 3-31 Observed turbidity at three compliance stations (Prisoner's Point, Holland Cut, and Victoria Canal).

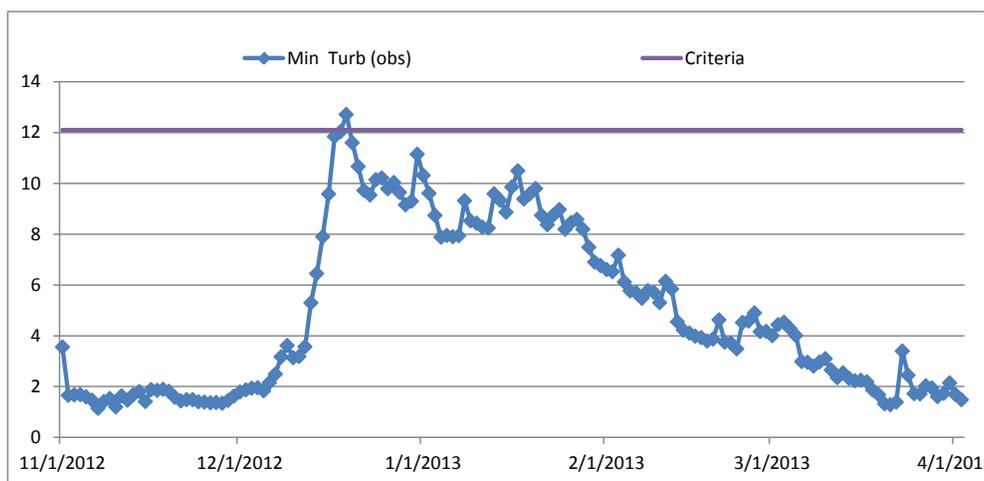


Figure 3-32 Daily minimum turbidity based on observations at three compliance stations in Figure 3-31. Each symbol corresponds to the minimum for a single day.

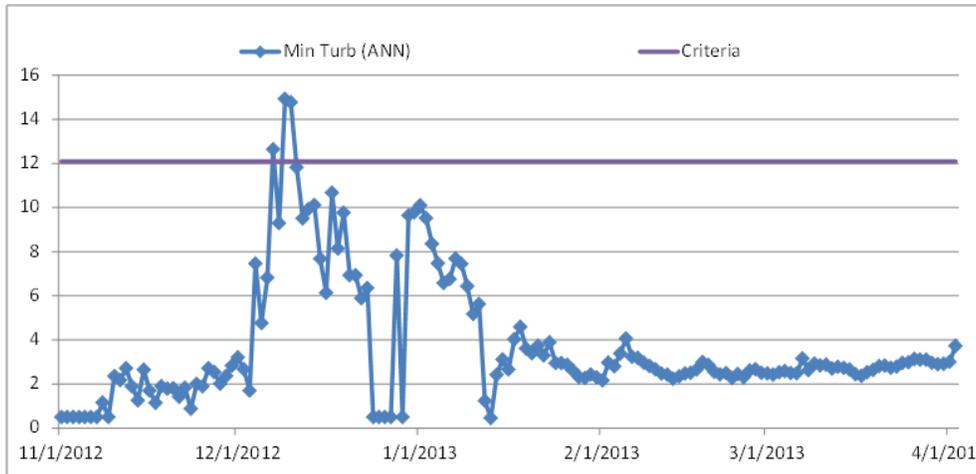


Figure 3-33 Daily minimum turbidity based on ANN predictions at three compliance stations in Figure 3-30. The ANN fits for these stations are discussed in Section 3.7.

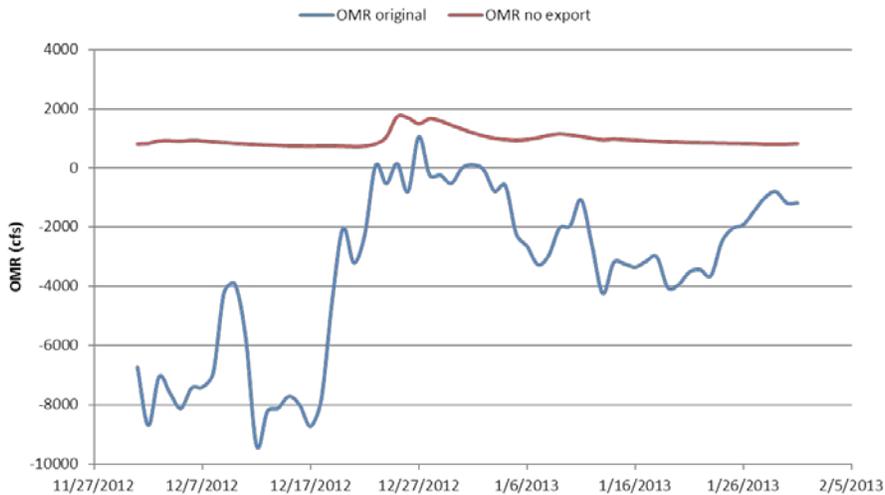


Figure 3-34 Range of OMR flow available for control. The blue line indicates the original, unmodified OMR flow. The red line is the OMR flow based on setting the exports to zero, using the Hutton (2008) approach discussed in the text.

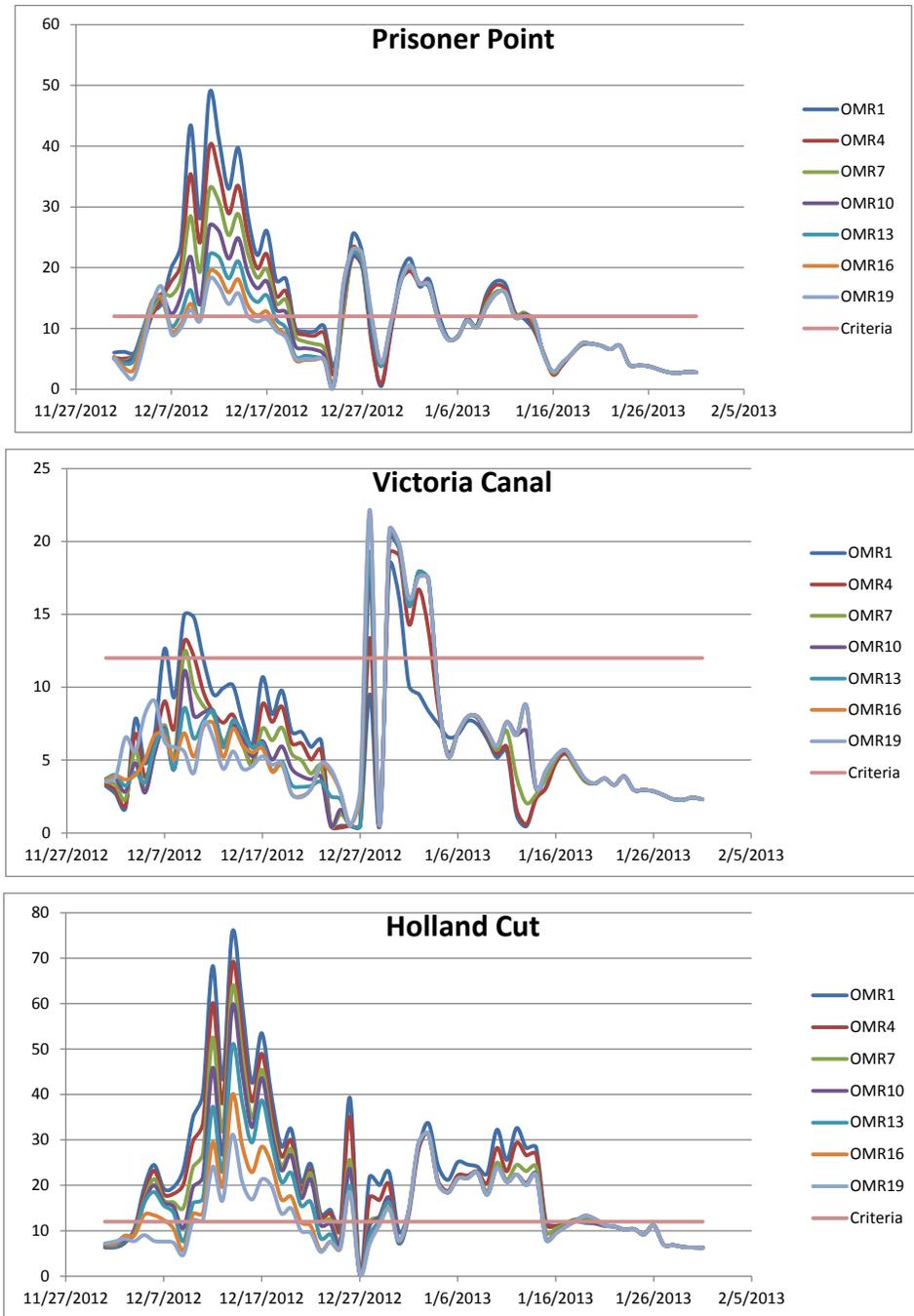


Figure 3-35 Simulated changes in turbidity at three stations due to OMR flow change. In all plots, OMR1 refers to the original OMR flow, and lines numbered OMR4 through OMR 19 refer to OMR flow changes in multiples 500 cfs. Thus, OMR4 represents a change of 4x500 cfs (2,000 cfs), and OMR 10 represents a change of 10x500 cfs (10,000 cfs).

4 SUMMARY AND DISCUSSION

The analysis presented here is the Phase 3 of a study to develop a turbidity ANN model for the Delta. Phase 2 and 3 of the study expand the first phase of the study to develop models at 16 locations within the Delta, and used an updated version of the DSM2 model to generate inputs and outputs for the ANN model. A total of 12 scenarios that take into account different levels of turbidity inputs at boundaries were used to generate the inputs to the ANN model.

The generated synthetic turbidity data were used to train feedforward network and the NARX network structures. The trained networks, when compared to DSM2 results, showed good emulation and were tested through correlations and evaluation of residuals against ANN inputs. The training process included a partitioning of the data such that a subset of the data was always used for validation and testing of the trained ANNs (both feedforward and NARX). The residuals analysis generally showed no correlation with flow or turbidity inputs, with higher residuals under lower flow. Further evaluation of the NARX network for a multi-year DSM2 simulation for the period of 1975-2011 showed good agreement. Evaluation was also performed for both the NARX and feedforward models using observed data for the 2012-13 wet season. The observed data were more challenging to fit using the ANNs, as discussed further below, although key features of the data, such as the peak turbidities were well represented. The NARX networks matched the magnitudes and durations of the observed turbidity peaks for this event reasonably well based on a visual comparison. The feedforward network fits, although not as good as the NARX fits, generally matched the same observed data. For predictive applications where only boundary conditions might be available, and the NARX model cannot be applied, such as the exercise of controlling turbidity through modification of OMR flow, the use of the feedforward network appears reasonable.

A sensitivity analysis of turbidities at various locations to OMR flow was conducted. The model showed different patterns of sensitivity to turbidity in different regions of the Delta. The West Delta stations showed no response or slight decrease in turbidity due to the increase of OMR flow. The Central Delta stations showed decreases in turbidity due

to increases in OMR flow, while the South Delta showed mixed results of increasing turbidity to OMR flow under high turbidity input from the San Joaquin River and the opposite trend under low turbidity input from the San Joaquin River. The sensitivity analysis provides insight on the ability of the water project operations (through management of OMR flows) to affect turbidity at specific locations.

Use of the trained ANN networks to forecast turbidity during the wet season of 2012-13 demonstrated that although the ANN networks closely followed DSM2 results, the forecasts strongly depend on quality of the underlying DSM2 simulation within the Delta. Thus, there were some locations for which the turbidity was underpredicted, or for which there was more rapid decline forecast than observed. This behavior was similar to that obtained from DSM2 for similar stations. In effect, the ANN performed well at representing DSM2 behavior under similar conditions. However, this behavior may not be matched by field observations. There are some mechanistic reasons for the underlying discrepancy. In particular, the first order decay for turbidity that is embodied in the DSM2 calibration may not be an adequate representation at all locations or under all conditions, where the observed data show turbidity levels remaining at elevated values for many days at a time. In contrast, other locations in the North Delta show rapid declines after a peak in turbidity that is well represented by both DSM2 and the ANN. An additional contributing factor may be processes such as wind and re-suspension that are not directly considered in the modeling. Finally, the training used a turbidity boundary of 20-110 NTU at Vernalis and 10 – 310 NTU at North Delta. Turbidity at these two locations for the forecast period (2013) may sometimes be outside the training range (lower or higher than the training range). Therefore in the future work, the actual low and high turbidity at the boundary should be used in the training.

Taken together, the ANN analysis as well as the review of the underlying DSM2 simulations, suggest two pathways for continued improvement of the quality of the turbidity forecasting in the Delta. A first step may consider additional calibration for DSM2, particularly focused on the stations that are required for turbidity compliance, to be followed by updated training. To a great extent, the three phases of turbidity ANN development represent this pathway. A second alternative may consider the exploration of ANNs using observed turbidity data as an alternative, and perhaps complementary, strategy to forecast near-term turbidity.

The current version of the feedforward ANN model was also used to explore conditions under which turbidity at selected compliance stations could be controlled by modifying the OMR flow. Using historical boundary flows and turbidities over 1975-2011 as inputs, the ANN model was first used to identify the potential exceedance events, and in each case, the OMR flow was changed until the turbidity was decreased to below the threshold of 12 NTU. It was found that OMR flow could only control a subset of the events (9 out of 37, over a 35-year period). Separately, the 2012-13 wet season turbidity was analyzed using the same approach. This differs from the other periods because of the

availability of observed data and the occurrence of high turbidities, conditions which came very close to it being considered a turbidity exceedance event using the definition of a three-station minimum turbidity exceeding 12 NTU for three continuous days. Because two of the three stations had high turbidities for several days, the three-station minimum was in fact exceeded only for one day, and, despite the visual impression, this does not fit the narrow definition of an exceedance event. This was true whether we looked at the observed data or the ANN-simulated data. The potential for turbidity control was explored because this event is recent and because of the high turbidities that resulted in two of the compliance stations (Prisoner's Point and Holland Cut). The OMR flow control approach shows that turbidity at these two stations could be decreased by changing the OMR flow but not below 12 NTU for the entire wet season. Although the turbidities are sensitive to OMR flow, in general, two factors preclude all events from being controlled: first, the range of available OMR flow for control is limited by the exports, and second, the relationship between OMR flow and turbidity is not monotonic, and in some cases reducing OMR flow may lead to higher turbidities at the compliance stations. These findings are of considerable importance for Delta operations, and next steps may include more mechanistic examination of the conditions where turbidity can and cannot be controlled.

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